CAUCHY – Jurnal Matematika Murni dan Aplikasi
Volume 10 (2) (2025), Pages 1349-1360
p-ISSN: 2086-0382; e-ISSN: 2477-3344

Mechanism Design-Based Mathematical Modeling of the Decoy Effect in Housing Type Selection

Sentot Eko Baskoro[1], I Nyoman Sutapa[2*], and Suhartono[3]

[1] *Management Department, STIE GICI Business School, Depok, Indonesia*
[2] *Industrial Engineering Department, Petra Christian University, Surabaya, Indonesia*
[3] *Informatics Engineering Department, Maulana Malik Ibrahim State Islamic University, Malang, Indonesia*

Abstract

This study develops a mechanism design-based mathematical model to induce a decoy effect in housing selection, shifting consumer preferences from small to large house types. Using an area-per-price utility function and dominance constraints, two optimal decoy configurations (adjacent and strong) are derived analytically. We consider a developer offering a small house (500,000,000 IDR; 40 m^2 building; 100 m^2 land) and a large house (1,000,000,000 IDR; 100 m^2 building; 200 m^2 land), and design an additional decoy alternative. By imposing dominance and feasibility constraints, we derive closed-form conditions on the decoy's building area A_d and land area L_d for two price levels, 750,000,000 IDR and 850,000,000 IDR. The resulting "adjacent" ($\Delta = 0.002$) and "strong" ($\Delta = 0.010$) decoys ensure that the large house weakly dominates the decoy while maintaining internal consistency of preferences. Sensitivity analysis shows that the advantage margin increases linearly with proximity and context intensity parameters. The proposed framework provides developers with an operational and auditable mechanism for housing portfolio design.

Keywords: attraction effect; asymmetric dominance; mechanism design; hous ing optimization; mathematical modeling.

1 Introduction

In many housing projects, small homes account for a large portion of sales because they are more affordable, while large homes, which are often more attractive to developers in terms of profit margins, have a relatively small market share. This situation raises a key question: how to design a portfolio of options that encourages consumers who initially lean toward small homes to switch to large homes [1], without compromising product integrity and without changing the specifications of the large homes themselves. One relevant behavioral approach is the decoy effect (asymmetric dominance), which is a strategy of inserting a comparison option that is slightly worse on certain attributes but close enough to the target option, so that the comparison becomes more favorable to the target [2]. On the other hand, from the perspective of Microeconomic theory, this issue can be viewed as a Mechanism Design problem: developers act as menu

*Corresponding author. E-mail: sentot.baskoro@stiegici.ac.id

Submitted: October 15, 2025 Reviewed: October 23, 2025 Accepted: November 29, 2025
DOI: https://doi.org/10.18860/cauchy.v10i2.36937

designers who determine the attributes of options under the constraints of consumer behavior and rationality [3], [4].

In the context of housing, the most basic set of attributes includes building area, land area, and price [5]. Consumers generally weigh the trade-off between "space" and "cost," with varying sensitivity to buildings and land [6]. To capture this in a concise yet informative manner, this study created a deterministic consumer utility mathematical model using area-per-price measures, namely building area and land area per unit price [7]. The weight of preference for each component is represented by the parameters α for buildings and β for land, with $\alpha, \beta \geq 0$ and $\alpha + \beta = 1$, following the practice of weighted additive utility functions [8]. In this way, a rational metric can be obtained that is transparent, interpretable, and easy to evaluate in various price and size scenarios.

While previous studies have examined the behavioral mechanism of asymmetric dominance, few have combined it with an explicit optimization framework based on mechanism design. This research bridges that gap by formulating a mathematical model that operationalizes consumer choice bias into parameterized utility functions. This study positions the decoy house as an additional option with specifications between small and large houses. The price of the decoy is set between the prices of the two types, while the decision variables are the building area A_d and land area L_d. The desired target is a decoy configuration that makes large houses appear "clearly superior" when compared directly, while keeping the decoy credible as a real option within the physical limits of the product [9]. Intuitively, the ideal decoy is "very close" to the large house but slightly lower on one or two value ratios so that the dominance of the large house is easily visible [10], [11].

A case study was taken to illustrate the operational and computational steps of the model. Large houses are priced at $P_b = 1$ billion IDR, with a building area of $A_b = 100$ m^2 and a land area of $L_b = 200$ m^2; small houses are priced at $P_s = 500$ million IDR, with a building area of $A_s = 40$ m^2 and a land area of $L_s = 100$ m^2. Thus, the building-to-price ratio of large houses is higher than that of small houses, while the land-to-price ratio of both is the same. Two decoy price alternatives are set at $P_{d1} = 750$ million IDR and $P_{d2} = 850$ million IDR. The design task is to determine the optimal (A_d, L_d) for each decoy price so that direct comparison tends to increase the attractiveness of large houses.

Methodologically, this article presents two layers of mathematical models. First, a general model that expresses the utility function $U_i = \alpha\frac{A_i}{P_i} + \beta\frac{L_i}{P_i}$ for each option $i \in \{s, d, b\}$ and formulates the decoy design problem as an optimization program based on "attribute proximity" with large houses under physical limits and dominance logic [9], [10]. Second, a case study application that fills in the parameters with real numbers, derives a closed-form solution (A_d, L_d) for two decoy prices, and calculates and discusses sensitivity analysis on the proximity parameter Δ and context intensity κ that represent the strength of the comparison effect in decision-making [12]. This sensitivity analysis is important from a managerial perspective because it shows how small changes in decoy specifications or consumer preference segmentation (α, β) can affect relative utility margins and, ultimately, choice behavior [4].

Existing research on the decoy (attraction) effect in consumer choice ([13], [14], [15]) has three key limitations: it is dominated by experimental and empirical studies that do not yield explicit design rules; it rarely incorporates binding physical and pricing constraints as in real housing portfolios; and it does not systematically connect behavioural context effects with mechanism design principles for incentive-compatible product structuring. As a result, developers lack a transparent, closed-form framework for specifying decoy alternatives that are both behaviourally effective and operationally auditable. This study addresses these gaps by proposing a mechanism design-based mathematical model for housing selection that embeds the decoy effect in an area-per-price utility with explicit dominance and feasibility constraints. The first contribution is a concise and replicable framework for designing decoy houses, yielding clear analytical conditions for (A_d, L_d). The second is the derivation of closed-form "adjacent" and "strong" decoy configurations at realistic price points, providing directly implementable parameter settings for practitioners. The third is a sensitivity analysis that integrates rational valuation (area-per-price) with behavioral salience parameters, enabling risk-weighted design decisions. Throughout, decoys will be framed as ethical choice architecture that clarifies attribute trade-offs for consumers [16]. The next section describes the methodology in detail, followed by results and discussion containing the optimal design and its implications, before concluding with conclusions and directions for further research.

2 Methods

This section describes the research design, mathematical model, optimization formulation, computational procedures, and evaluation and sensitivity analysis plans. The focus is on determining the attributes of decoy houses, namely the building area A_d and land area L_d, at a specific decoy price $P_d \in \{P_s, P_b\}$ in order to encourage consumers to shift their preferences to larger houses.

The research is quantitative-theoretical with four steps. First, it formulates a concise yet informative utility function for house area per price [8]. Second, it defines asymmetric dominance criteria that make the decoy house "appear worse" than the large house (big) but not dominated by the small house (small) [9], [10]. third, developing an optimization program to select (A_d, L_d) that is closest to big in the value ratio space (so that the comparison favors big) [4]; fourth, conducting a sensitivity analysis of preference parameters (α, β), proximity levels (Δ_a, Δ_l), and decoy prices P_d [10]. Parameters α and β are building and land preference weights, respectively.

For each option $i \in \{s, d, b\}$ (where s for small, d for decoy, and b for big house), the following are defined: P_i as the house price, A_i as the house floor area, and L_i as the house land area. Furthermore, the floor area-to-price ratio is set as $a_i = A_i/P_i$ and the land area-to-price ratio as $l_i = L_i/P_i$. The consumer preference type is defined as $\theta = (\alpha, \beta)$ with weights $\alpha, \beta \geq 0$ and $\alpha + \beta = 1$.

The utility function is defined as [8]:

$$U_i(\theta) = \alpha a_i + \beta l_i = \alpha \frac{A_i}{P_i} + \beta \frac{L_i}{P_i} \quad \text{where } i = \{s, d, b\} \tag{1}$$

Assuming: first, consumers choose the option with the highest utility (self-selection) [17]; second, there is no individual price discrimination [4]; third, the decoy house is a viable product and meets physical constraints [10] $A_s \leq A_d \leq A_b,\ L_s \leq L_d \leq L_b$.

As a case study to clarify the Mathematical Model, the following parameters were set: a large house with a price of $P_b = 1$ billion IDR, building area $A_b = 100\,\mathrm{m}^2$, and land area $L_b = 200\,\mathrm{m}^2 \Rightarrow a_b = 0.10, l_b = 0.20$. A small house with a price of $P_s = 500$ million IDR, building area $A_s = 40\,\mathrm{m}^2$, and land area $L_s = 100\,\mathrm{m}^2 \Rightarrow a_s = 0.08, l_s = 0.20$. Furthermore, a decoy house with a price of $P_{d1} = 750$ million IDR and $P_{d2} = 850$ million IDR.

The initial implication is that the big house has an advantage in terms of building area per price, i.e., $a_b > a_s$, and is on par in terms of land area per price, $l_b = l_s$. This situation opens up the possibility of a classic asymmetric decoy by selecting $a_d \in (a_s, a_b]$ and $l_d \leq l_b$.

Determination of asymmetric dominance criteria and feasible sets. In order for big to dominate decoy, but small not to dominate decoy house, big is defined as dominating decoy if $a_d \leq a_b$ and $l_d \leq l_b$ (at least one strict condition). Small does not dominate decoy if it is not true that $a_d \leq a_s$ and $l_d \leq l_s$ simultaneously. Since $l_s = l_b$, it is sufficient to ensure that $a_d > a_s$.

The next physical and price constraints yield a feasible set, namely

$$A_s \leq A_d \leq A_b, \quad L_s \leq L_d \leq L_b, \quad P_s < P_d < P_b \tag{2}$$

In the ratio space, the boundary (2) becomes:

$$\frac{A_s}{P_d} \leq a_d \leq \min\left\{\frac{A_b}{P_d}, a_b\right\}, \quad \frac{L_s}{P_d} \leq l_d \leq \min\left\{\frac{L_b}{P_d}, l_b\right\} \tag{3}$$

For the first decoy price case, $P_{d1} = 750$, we obtain $a_d \in [0.053, 0.100]$ and $l_d \in [0.133, 0.200]$. Meanwhile, for the second decoy price case, $P_{d2} = 850$, we obtain $a_d \in [0.047, 0.100]$ and $l_d \in [0.118, 0.200]$. The main anti-domination condition for small requires that $a_d > a_s = 0.08$.

Optimization formulation or "adjacent" decoy. The decoy house will be very close to the big house so that the advantages of the big house are easily visible in a direct comparison [10]. The distance is measured in space (a, l). Define the degree of "controlled regression" of the decoy from the big house as [9]:

$$\Delta_a = a_b - a_d \ (\geq 0), \quad \Delta_l = l_b - l_d \ (\geq 0) \tag{4}$$

The optimization problem can be formulated as

$$\min_{\Delta_a, \Delta_l} w_a \Delta_a^2 + w_l \Delta_l^2 \tag{5}$$

subject to the constraints:

$$\Delta_a \geq 0,\ \Delta_l \geq 0 \text{ neither } 0, \qquad \text{big dominance} \tag{6}$$

$$a_d = a_b - \Delta_a > a_s, \qquad \text{anti-domination small} \tag{7}$$

$$A_s \leq A_d \leq A_b,\ L_s \leq L_d \leq L_b, \qquad \text{physical boundaries} \tag{8}$$

$$A_d = a_d, P_d = (a_b - \Delta_a)P_d, L_d = l_d P_d = (l_b - \Delta_l)P_d, \qquad \text{by definition} \tag{9}$$

with weight $w_a, w_l > 0$ allows emphasis on proximity to one ratio (default where $w_a = w_l = 1$).

The solution to the optimization model (objective 5 with constraints 6-9) is closed-form [18]. Since the objective function is convex and the constraints are linear, the optimal solution always lies on the constraint boundary (corner) [19]. With $w_a = w_l$, the minimal choice is the one that makes Δ_a, Δ_l as small as possible while satisfying the condition:

$$\Delta_a \geq 0,\ \Delta_l \geq 0 \text{ and } (\Delta_a > 0) \vee (\Delta_l > 0) \tag{10}$$

$$a_b - \Delta_a > a_s \Rightarrow \Delta_a < a_b - a_s \text{ (in this case } < 0.02) \tag{11}$$

$$A_s \leq (a_b - \Delta_a)P_d \Rightarrow \Delta_a \leq a_b - \frac{A_s}{P_d} \tag{12}$$

$$L_s \leq (l_b - \Delta_l)P_d \Rightarrow \Delta_l \leq l_b - \frac{L_s}{P_d} \tag{13}$$

Thus, for each P_d, the smallest feasible and non-simultaneously zero Δ_a and Δ_l can be selected. In practice, two patterns are often used, namely the balanced adjacent design, which is a small $\Delta_a \equiv \Delta_l$ (making the decoy "almost" big in two ratios). The weighted design is $\Delta_a \neq \Delta_l$ to adjust the segment (for example, β is large $\rightarrow$ make Δ_l slightly larger so that the dominance of big on the land is more apparent) [9], [10]. Furthermore, the physical decision value is:

$$A_d = (a_b - \Delta_a)P_d, \quad L_d = (l_b - \Delta_l)P_d \tag{14}$$

Adding context utility (attraction/salience). The comparison effect often increases the attractiveness of the target option when the target appears better on the same attribute [20], [10]. To capture this parsimoniously, big utility is extended [12]:

$$U_b^{tk} = U_b + \kappa(\alpha\Delta_a + \beta\Delta_l), \qquad \kappa \geq 0 \tag{15}$$

so that the margin relative to small becomes:

$$U_b^{tk} - U_s = \underbrace{\alpha(a_b - a_s)}_{\text{base margin}} + \kappa(\alpha\Delta_a + \beta\Delta_l) \tag{16}$$

In the case study, the baseline margin is 0.02, because $l_b = l_s$. The context component is proportional to the "controlled distance" between the big and decoy houses on the dimension relevant to preference weight (α, β) [9], [10].

For each decoy price $P_d \in \{P_{d1}, P_{d2}\}$, the calculation steps can be determined, namely:
Step 1. Calculate the base ratio: a_b, l_b, a_s, l_s.
Step 2. Calculate the Δ limit of the physical product:

$$\Delta_a^{\max} = a_b - \max\left(a_s, \frac{A_s}{P_d}\right), \qquad \Delta_l^{\max} = l_b - \frac{L_s}{P_d} \tag{17}$$

Step 3. Select the proximity scheme, namely balanced adjacent, i.e., choose a small Δ (> 0) then set $\Delta_a = \min(\Delta, \Delta_a^{\max})$, $\Delta_l = \min(\Delta, \Delta_l^{\max})$. Set the small Δ_a, Δ_l weights differently according to the target segment (e.g., high $\beta \to$ increase Δ_l relative to Δ_a). Ensure that $\Delta_a < a_b - a_s$ so that $a_d > a_s$ (anti-domination of small) [9], [10].
Step 4. Calculate the physical decision, namely

$$A_d = (a_b - \Delta_a)P_d, \quad L_d = (l_b - \Delta_l)P_d \tag{18}$$

Step 5. Verify feasibility: $A_s \leq A_d \leq A_b$ and $L_s \leq L_d \leq L_b$. If violated, reduce Δ or adjust Δ_a/Δ_l.
Step 6. (Optional) Evaluate the margin $U_b^{ctx} - U_s$ in the scenario (α, β, κ) to assess the strength of the effect [12].

Set performance metrics, proximity ratio, namely Δ_a, Δ_l (the smaller the better). Utility margin, namely $U_b^{ctx} - U_s$ on the grid (α, β) and κ representative. Dominance compliance, check big $>$ decoy and small $\not>$ decoy. As well as physical feasibility, namely A_d, L_d within $[A_s, A_b] \times [L_s, L_b]$. The Utility Margin formula as follows:

$$\Delta U = U_{big} - U_{small} = \alpha\frac{A_b}{P_b} + \beta\frac{L_b}{P_b} - \left(\alpha\frac{A_s}{P_s} + \beta\frac{L_s}{P_s}\right) \tag{19}$$

Mechanism-design linkage: Individual Rationality (IR) and Incentive Compatibility (IC). The Individual Rationality (participation) requirement is that, for every type θ,

$$\max_{i \in \{s,d,b\}} U_i(\theta) \geq U_0(\theta) = 0. \tag{20}$$

Under the present specification, all ratios a_i, l_i are nonnegative (strictly positive in the case study), and the preference weights satisfy $\alpha, \beta \geq 0$ and $\alpha + \beta = 1$. Hence

$$U_i(\theta) = \alpha a_i + \beta l_i \geq 0 \quad \forall\, i \in \{s, d, b\},\ \theta \in \Theta, \tag{21}$$

so that IR constraint (20)–(21) is automatically satisfied for every consumer type as soon as at least one house is under consideration. In other words, the IR constraint does not restrict the decoy-design problem beyond the physical feasibility conditions already imposed in (2)–(3): consumers can always decline to purchase if all utilities were too low, and the case-study calibration focuses on segments for which buying a house is already individually attractive.

Incentive Compatibility (IC) and self-selection. For a posted-menu mechanism with no type-dependent pricing, Incentive Compatibility reduces to rational self-selection: each consumer simply chooses the option in M that yields the highest utility given their type θ. Formally, the IC condition can be written as choice rule:

$$i^*(\theta) \in \arg\max_{i \in \{s,d,b\}} U_i(\theta), \quad \forall\theta \in \Theta \quad \text{(IC-general)} \tag{22}$$

There is no informational misreporting in this environment, because consumers do not communicate their type to the developer; they only pick from the publicly offered menu. Thus (22) is satisfied by construction whenever consumers behave according to utility maximization (self-selection assumption).

For the specific segment of interest, denoted $\Theta^{\text{big}} \subset \Theta$, the developer aims to implement the big house as the preferred alternative. The corresponding segment-wise IC requirements are

$$U_b(\theta) \geq U_s(\theta), \quad U_b(\theta) \geq U_d(\theta), \ \forall \theta \in \Theta^{\text{big}} \quad \text{(IC-big)} \tag{23}$$

Using the linear utility $U_i(\theta) = \alpha a_i + \beta l_i$ and nonnegative weights α, β, a sufficient condition for (23) is that the big house weakly dominates the decoy in both ratios (with at least one strict inequality),

$$a_b \geq a_d, \quad l_b \geq l_d, \text{ and } (a_b > a_d \text{ or } l_b > l_d) \quad \text{big-dominance} \tag{24}$$

while the small house does not dominate the decoy, e.g.

$$not(a_s \geq a_d \text{ and } l_s \geq l_d) \quad \text{(small-anti)} \tag{25}$$

Conditions (24)–(25) are exactly the dominance and anti-domination constraints (6)–(7) expressed in ratio space. Under these constraints, any type $\theta \in \Theta^{\text{big}}$ that already finds the big house at least as attractive as the small one in terms of area-per-price will weakly prefer b to d and s, so that (IC-big) holds automatically.

The IR and IC conditions of mechanism design can be written for this setting as (20)–(22), with the segment-specific IC inequalities (23). Given the monotone, additive utility structure and the feasibility region defined by (2)–(3), the IR constraint is non-binding and the IC requirements are enforced through the dominance and anti-domination constraints (6)–(7). Therefore, explicit IR/IC terms do not alter the optimization program (5); instead, they provide an interpretive mechanism-design lens on the existing constraints.

From a managerial standpoint, IR means that the housing menu must remain attractive enough that buyers still feel they are getting "sufficient space for the price" compared with the outside option. The model incorporates this by working with positive area-per-price utilities and realistic physical bounds, so that all three units (small, decoy, big) remain credible purchase options. IC reflects voluntary self-selection: given the advertised specifications and prices, each buyer freely chooses the alternative that best matches their own trade-off between building area and land. The role of the decoy design is not to force anyone into the big house, but to structure the menu so that, for the targeted segment, the large unit transparently appears as the best-value choice: it dominates the decoy on the same attributes and remains sufficiently differentiated from the small unit. In this sense, the decoy specification derived from (5) can be interpreted as an incentive-compatible "choice architecture" those nudges, rather than coerces, buyers toward larger houses while preserving product feasibility and transparency.

Sensitivity analysis was first conducted on the decoy price of million price P_d, which affects the feasibility threshold $\Delta_a^{\max}, \Delta_l^{\max}$ through $\frac{A_s}{P_d}$ and $\frac{L_s}{P_d}$ [4]. Second, the proximity (Δ_a, Δ_l), which linearly affects the margin context $(\alpha\Delta_a + \beta\Delta_l)$ but is constrained by physical feasibility [20]. Third, the preference (α, β), which alters the contribution of each ratio to utility. Segments with high β tend to respond to Δ_l [8], [17]. Fourth, the strength of context κ, which increases the influence of proximity on margins, is relevant to information presentation strategies [12]. For the case study [18], this article presents margins on a grid at $\alpha \in \{0.2, 0.4, 0.6, 0.8, 1.0\}$, $\Delta \in \{0.002, 0.005, 0.010, 0.015, 0.020\}$, and κ representative (e.g., $\kappa = 1$ as normalization), for both P_d.

The robustness and validity of the model were tested using construct and physical robustness test as well as validity tests. Construct robustness was tested using a weighted scenario test $w_a \neq w_l$ on the objective function; selecting Δ at the upper limit of feasibility when one dimension was to be emphasized [21], [22], [23], [19]. Physical robustness was tested using sensitivity tests on the limits A_s, A_b, L_s, and L_b [22], [21]. Meanwhile, the validity of the model was evaluated using the area-per-price metric, which was chosen for its transparency and ease of auditing [8], [7].

3 Results and Discussion

3.1 Result

As an explanation of the Mathematical Model that has been developed, here is a case study, with the following case settings. A large house type with a price of $P_b = 1{,}000$ million, building area $A_b = 100$ m^2, and land area $L_b = 200$ m^2 so that $a_b = 0.10$ and $l_b = 0.20$. A small house type with a price of $P_s = 500$ million, building area $A_s = 40$ m^2, and land area $L_s = 100$ m^2 so that $a_s = 0.08$ and $l_s = 0.20$. Two decoy prices are set at $P_{d1} = 750$ million and $P_{d2} = 850$ million. The base margin of big over small in the general model is $U_b - U_s = \alpha(a_b - a_s) + \beta(l_b - l_s) = 0.02$, because $l_b = l_s$. This means that even without the decoy, big already leads in the building-per-price dimension when $\alpha > 0$, but it is not yet prominent in the land-per-price dimension.

Feasible set and dominance implications. Physical constraints $A_s \le A_d \le A_b$, $L_s \le L_d \le L_b$ and big dominance $(a_d \le a_b, l_d \le l_b)$ give a range of ratios that can be selected, namely

- For $P_{d1} = 750$ million, we obtain $a_d \in [40/750, 0.10] = [0.0533, 0.10]$, $l_d \in [100/750, 0.20] = [0.1333, 0.20]$.
- For $P_{d2} = 850$ million, we obtain $a_d \in [40/850, 0.10] = [0.0471, 0.10]$, $l_d \in [100/850, 0.20] = [0.1176, 0.20]$.

To prevent the small from dominating the decoy, simply require $a_d > a_s = 0.08$ (since $l_s = l_b$). Thus, the classical asymmetric decoy construction is possible, i.e., choose $a_d \in (0.08, 0.10]$ m^2 and $l_d \le 0.20$.

Closed-form solutions and two operational designs. With the objective of squared proximity $(a_b - a_d)^2 + (l_b - l_d)^2$, the solution lies within the constraint boundaries. For balanced proximity weights, this article identifies two practical proximity levels that can be used in the field, namely

- Adjacent (very close): $\Delta_a = \Delta_l = 0.002 \Rightarrow a_d = 0.098,\ l_d = 0.198$.
- Strong (more stringent): $\Delta_a = \Delta_l = 0.010 \Rightarrow a_d = 0.090,\ l_d = 0.190$.

The physical dimensions of the decoy (A_d, L_d) are obtained from $A_d = (a_b - \Delta_a)P_d$ and $L_d = (l_b - \Delta_l)P_d$, namely:

For the decoy price of $P_{d1} = 750$ million, the solutions for the building area and land area of the decoy house are:

- Adjacent: $A_d = 0.098 \times 750 = 73.5$ m^2, $L_d = 0.198 \times 750 = 148.5$ m^2.
- Strong: $A_d = 0.090 \times 750 = 67.5$ m^2, $L_d = 0.190 \times 750 = 142.5$ m^2.

For the decoy price of $P_{d2} = 850$ million, the solution for the building area and land area of the decoy house is:

- Adjacent: $A_d = 0.098 \times 850 = 83.3$ m^2, $L_d = 0.198 \times 850 = 168.3$ m^2.
- Strong: $A_d = 0.090 \times 850 = 76.5$ m^2, $L_d = 0.190 \times 850 = 161.5$ m^2.

All solutions satisfy the physical constraints $(40 \le A_d \le 100,\ 100 \le L_d \le 200)$, big dominance (since $\Delta_a, \Delta_l \ge 0$ and at least one is strict), and small anti-dominance (since $a_d > 0.08$).

The utility margin is context-dependent. With context expansion $U_b^{ctx} = U_b + \kappa(\alpha\Delta_a + \beta\Delta_l)$, the total margin becomes $U_b^{ctx} - U_s = 0.02\alpha + \kappa(\alpha\Delta_a + \beta\Delta_l)$. For a balanced design $\Delta_a = \Delta_l = \Delta$, the simple margin is obtained as $0.02\alpha + \kappa\Delta$. Numerical example at $\kappa = 1$:

- Adjacent $\Delta = 0.002$ yields a margin of $= 0.02\alpha + 0.002$.

- Strong $\Delta = 0.010$ yields a margin of $= 0.02\alpha + 0.010$.

With $\alpha = 0.4$, for example, the margin is adjacent $= 0.008 + 0.002 = 0.010$, while strong $= 0.008 + 0.010 = 0.018$.

The following Table 1 shows decoy land areas L_d (in m^2) for two decoy price levels, $P_d =$ 750 million IDR and $P_d = 850$ million IDR, under two proximity settings. The "adjacent" configuration uses $\Delta = 0.002$ and the "strong" configuration uses $\Delta = 0.010$, with $L_d = (l_b - \Delta)P_d$ and $l_b = L_b/P_b = 0.20$ based on $L_b = 200\text{m}^2$ and $P_b = 1{,}000$million IDR.

Table 1: Decoy land areas for two price levels and proximity settings

Proximity level	Δ	L_d ($P_d = 750$ M IDR) [m^2]	L_d ($P_d = 850$ M IDR) [m^2]
Adjacent	0.002	148.5	168.3
Strong	0.010	142.5	161.5

Small illustration to show how proximity and context parameters affect results. Without a decoy, the big house is only slightly better than the small one, so many buyers can still justify choosing the small unit. A very close decoy (small Δ) that is dominated by the big house but not by the small one makes the big house look like the "smart upgrade" with minimal extra sacrifice, especially when even mild context effects ($\alpha\Delta_a + \beta\Delta_l$) are present. A stronger decoy (larger Δ) and/or stronger context (larger ($\alpha\Delta_a + \beta\Delta_l$)) amplifies the utility gap in favor of the big house, increasing its attractiveness, but if Δ is too large the decoy stops looking credible, so there is a practical trade-off between proximity and persuasive impact.

3.2 Discussion

Practical optimization and clear readability. Mathematically, the "smallest" proximity that still satisfies dominance (e.g., $\Delta_a \downarrow 0^+, \Delta_l = 0$) minimizes the distance. However, in marketing practice, *salience* is needed to make the difference clearly visible. That is why two levels of proximity are reported: *adjacent* (conservative, high similarity) and *strong* (more prominent). Both maintain product credibility (realistic specifications) while making the big advantage easy to grasp when comparing two identical ratios [9], [10].

The role of decoy pricing. An increase in P_d proportionally raises A_d and L_d without altering the ratio a_d, l_d. Since utility is ratio-based, the "proximity" perceived by consumers remains controlled by Δ, not by the absolute level A_d, L_d. Thus, the choice of P_d is more related to the *price position* in the portfolio and the physical suitability of the land, while the persuasive effect is primarily regulated by Δ and κ [12], [20].

Preference segmentation. The base margin 0.02α shows that markets more focused on buildings (large α) are relatively friendly to big. In segments more focused on land (large β), the context component κ, Δ_l becomes crucial; *strong* design provides a larger margin with proximity costs (the product is slightly "behind" big on both ratios) [17], [6].

Physical boundaries and anti-cannibalization. All solutions maintain $A_d < L_b$ and $L_d < L_b$, while ensuring ($a_d > a_s$) so that the decoy does not become a "cheap version" of the small house. This is important to prevent uncontrolled cannibalization of the small house market share and maintain the migration path of preferences toward the big house [3], [4].

Sensitivity of Δ and κ. Since $U_b^{ctx} - U_s$ increases linearly with Δ and κ, developers can balance "design distance" and "communication strength" (presentation, framing, brochure/show unit layout). If operational κ is estimated to be low, choose a slightly larger Δ (strong); if κ is high (e.g., effective product education), a small Δ (adjacent) is sufficient [10], [24].

To illustrate how proximity Δ and the context parameter κ jointly affect the big vs. small utility margin, we use the case-study data. The physical attributes and prices are $(A_b, L_b, P_b) =$ $(100, 200, 1000)$, $(A_s, L_s, P_s) = (40, 100, 500)$, so that the area-per-price ratios in (1) are $a_b =$ $A_b/P_b = 0.10$, $l_b = L_b/P_b = 0.20$, $a_s = A_s/P_s = 0.08$, $l_s = L_s/P_s = 0.20$.

For a representative balanced-decoy scheme, the decoy ratios are parameterised by a proximity distance $\Delta > 0$ as

$$a_d(\Delta) = a_b - \Delta, \quad l_d(\Delta) = l_b - \Delta, \tag{26}$$

which is consistent with the adjacent and strong designs reported in (11)–(13). The feasibility bound in (17) yields $0 < \Delta \leq \Delta^{\max} := \min\{a_b - a_s,\ l_b - L_s/P_d\} \approx 0.02$, so the values $\Delta \in \{0.002, 0.010\}$ used below lie well inside the admissible range.

For any preference type $\theta = (\alpha, \beta)$, with $\alpha, \beta \geq 0$ and $\alpha + \beta = 1$, the baseline (no-context) utility of option $i \in \{s, d, b\}$ is $U_i(\alpha, \beta) = \alpha a_i + \beta l_i$, and the baseline big vs. small margin is

$$\Delta U_0(\alpha, \beta) := U_b(\alpha, \beta) - U_s(\alpha, \beta). \tag{27}$$

Consistent with (15)–(16), context (attraction/salience) is captured by extending the big-house utility with a fraction $\kappa \in [0, 1]$ of its advantage over the decoy,

$$U_b^{ctx}(\alpha, \beta; \Delta, \kappa) := U_b(\alpha, \beta) + \kappa(U_b(\alpha, \beta) - U_d(\alpha, \beta; \Delta)), \tag{28}$$

where $U_d(\alpha, \beta; \Delta)$ is computed from (26). The corresponding context-augmented big vs. small margin is

$$\Delta U(\alpha, \beta; \Delta, \kappa) := U_b^{ctx}(\alpha, \beta; \Delta, \kappa) - U_s(\alpha, \beta) = \Delta U_0(\alpha, \beta) + \kappa(U_b(\alpha, \beta) - U_d(\alpha, \beta; \Delta)) \tag{29}$$

All utility values are in area-per-price units (m^2/million IDR), consistent with (1).

We then sweep Δ and κ over the grid $\Delta \in \{0.002, 0.010\}$, $\kappa \in \{0, 0.5\}$, for two representative preference profiles: (i) a balanced type $(\alpha, \beta) = (0.5, 0.5)$, and (ii) a building-focused type $(\alpha, \beta) = (0.7, 0.3)$.

The resulting baseline and context-augmented margins are summarised in Table 2, which show how the utility margin ΔU, the difference between the big option's utility and the small option's utility, is affected by the decoy proximity parameter Δ and the context parameter κ, across two different preference profiles (α, β).

Comparison with the literature. Conceptually, these results are consistent with findings of *asymmetric dominance* effects: a decoy that is close and slightly inferior on the same attribute increases the choice of the target. The novelty here is the closed formula (A_d, L_d) that links physical specifications, price, and preference weights into an operational recipe for two decoy price points [9], [10].

Table 2: Sensitivity of Δ and κ

Preference Profile (α, β)	Decoy Proximity (Δ)	Context Parameter (κ)	Baseline Margin ΔU_0	Context Margin $\Delta U(\Delta, \kappa)$
(0.5, 0.5)	0.002	0.0	0.010	0.010
(0.5, 0.5)	0.002	0.5	0.010	0.011
(0.5, 0.5)	0.010	0.0	0.010	0.010
(0.5, 0.5)	0.010	0.5	0.010	0.015
—	—	—	—	—
(0.7, 0.3)	0.002	0.0	0.014	0.014
(0.7, 0.3)	0.002	0.5	0.014	0.015
(0.7, 0.3)	0.010	0.0	0.014	0.014
(0.7, 0.3)	0.010	0.5	0.014	0.019

Implications. For $P_{d1} = 750$ and $P_{d2} = 850$ million, the operationally optimal decoy specifications (adjacent: $\Delta = 0.002$; strong: $\Delta = 0.010$) yield credible measures, satisfy all constraints, and measurably increase the target's utility margin. The choice between *adjacent* and *strong* can be determined by estimates (α, β), target *salience* κ, and pricing strategies within the portfolio.

From an ethical perspective, the decoy effect (also known as asymmetric dominance), a robust behavioural phenomenon, occurs when the introduction of a clearly inferior third option (the decoy) shifts preference between two existing options (the target and the competitor). The use of decoy pricing raises several ethical questions. Critics argue that it manipulates consumers' choices and may lead them to make decisions they wouldn't otherwise make. There's a fine line between nudging customers towards a particular option and exploiting cognitive biases to drive sales. Ethical concerns become particularly pronounced when decoy pricing is used in essential services or products that have significant impact consumers' lives. For instance, using such strategies in healthcare plans or financial products could be seen as taking advantage of consumers in vulnerable situations [25].

4 Conclusion

This mathematical model presents a concise and executable mechanistic for designing decoy houses so that consumer preferences shift from small-type houses to large-type houses [9], [10]. With area-per-price utility combining building-per-price and land-per-price, the problem is formulated as attribute selection (A_d, L_d) at a medium price P_d under dominance, anti-dominance, and physical product constraints [4]. In thecase study, it can be shown that the big house excels in building-per-price and is balanced in land-per-price, so that a classic asymmetric decoy can be constructed by choosing a_d between the small and big values and l_d not exceeding that of the big house.

The closed-form solution yields two simple operational mechanisms, an adjacent design with small proximity (Δ_a, Δ_l) to maintain high similarity, and a strong design with greater proximity to emphasize comparison [9], [10]. In the case study, two decoy house prices were set, obtained both mechanisms provide realistic physical sizes, satisfy the bounds $[A_s, A_b] \times [L_s, L_b]$, and ensure that big dominates the decoy while small does not. When context utility is factored in, the margin of big's advantage increases linearly with proximity level and salience parameter κ, above the baseline margin derived from building dimensions [12]. These results provide clear design levers: adjust Δ to manage product "distance," and adjust κ through information presentation, education, and marketing materials.

In practical terms, developers can choose adjacent for segments that already relatively value building area, and switch to strong for segments that demand more emphasis on attribute comparisons. From a scientific perspective, this framework combines simple rationality with measurable context effects, thereby facilitating calibration and auditing [8]. The main limitation is the exclusion of non-physical attributes such as location, material quality, credit access, and heterogeneity of preferences. Future research should empirically validate the proposed decoy house model using observed housing sales data and carefully designed consumer choice surveys. Furthermore, ethical aspects must be emphasized: decoys should be transparent information architecture that benefits consumers, not tools to obscure product quality [16]. Thus, this approach is ready to be used as a guideline for accountable and effective housing portfolio design.

CRediT Authorship Contribution Statement

Sentot Eko Baskoro: Conceptualization, Methodology, Formal Analysis, Writing–Original Draft, Visualization. I Nyoman Sutapa: Validation, Supervision, Writing–Review and Editing, Project Administration. Suhartono: Methodology, Validation, Supervision, Writing–Review and Editing.

Declaration of Generative AI and AI-assisted technologies

The authors declare that no generative AI or AI-assisted tools were used to create, analyze, or interpret the research results in this article. Generative AI tools were used solely for minor language refinement at the proofreading stage, under the direct supervision and full responsibility of the authors. All scientific content, analysis, and conclusions were produced entirely by the authors.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

Funding and Acknowledgments

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The authors would like to thank the respective institutions for their support during the completion of this study.

Data and Code Availability

The study is based entirely on analytical and mathematical modeling. No empirical dataset was used in the analysis. All formulas, derivations, and computational procedures required to reproduce the results are fully described within the article. Supplementary calculation scripts used to verify numerical examples can be provided by the corresponding author upon reasonable request.

References

[1] M. Weinmann, A. N. Mishra, L. F. Kaiser, and J. vom Brocke, "The attraction effect in crowdfunding," *Information Systems Research*, vol. 34, no. 3, pp. 1276–1295, 2022. DOI: 10.1287/isre.2022.1152.

[2] G. Castillo, "The attraction effect and its explanations," *Games and Economic Behavior*, vol. 119, pp. 123–147, 2020. DOI: 10.1016/j.geb.2019.10.012.

[3] S. P. Anderson and L. Celik, "Product line design," *Journal of Economic Theory*, vol. 157, pp. 517–526, 2015. DOI: 10.1016/j.jet.2015.01.014.

[4] M. Armstrong, "Nonlinear pricing," *Annual Review of Economics*, vol. 8, pp. 583–614, 2016. DOI: 10.1146/annurev-economics-080614-115650.

[5] J. Zabel, "The hedonic model and the housing cycle," *Regional Science and Urban Economics*, vol. 54, pp. 74–86, 2015. DOI: 10.1016/j.regsciurbeco.2015.07.005.

[6] C. d. S. Hentschke, P. A. Tillmann, C. T. Formoso, V. L. M. Martins, and M. E. S. Echeveste, "Using conjoint analysis to understand customer preferences in customized low-income housebuilding projects," *Ambiente Construído*, vol. 20, no. 1, pp. 247–262, 2020. DOI: 10.1590/S1678-86212020000100372.

[7] D. Stenvall, P. Cerin, B. Sjö, and G. S. Uddin, "Does energy efficiency matter for prices of tenant-owned apartments?" *Environmental Science and Pollution Research*, vol. 29, pp. 66 793–66 807, 2022. DOI: 10.1007/s11356-022-20482-w.

[8] I. Kaliszewski and D. Podkopaev, "Simple additive weighting—a metamodel for multiple criteria decision analysis methods," *Expert Systems with Applications*, vol. 54, pp. 155–161, 2016. DOI: 10.1016/j.eswa.2016.01.042.

[9] T. Dumbalska, V. Li, K. Tsetsos, and C. Summerfield, "A map of decoy influence in human multialternative choice," *Proceedings of the National Academy of Sciences*, vol. 117, no. 40, pp. 25 169–25 178, 2020. DOI: 10.1073/pnas.2005058117.

[10] J. Liao, Y. Chen, W. Lin, and L. Mo, "The influence of distance between decoy and target on context effect: Attraction or repulsion?" *Journal of Behavioral Decision Making*, vol. 34, no. 3, pp. 432–447, 2021. DOI: 10.1002/bdm.2220.

[11] P. K. Padamwar, J. Dawra, and V. K. Kalakbandi, "The impact of range extension on the attraction effect," *Journal of Business Research*, vol. 126, pp. 565–577, 2021. DOI: 10.1016/j.jbusres.2019.12.017.

[12] M. Usher, K. Tsetsos, M. Glickman, and N. Chater, "Selective integration: An attentional theory of choice biases and adaptive choice," *Current Directions in Psychological Science*, vol. 28, no. 6, pp. 552–559, 2019. DOI: 10.1177/0963721419862277.

[13] P. G. Hansen and A. M. Jespersen, "Nudge and the manipulation of choice," *European Journal of Risk Regulation*, vol. 4, no. 1, pp. 3–28, 2013. DOI: 10.1017/S1867299X00002762.

[14] P. Michaelsen, "Transparency and nudging: An overview and methodological critique of empirical investigations," *Behavioural Public Policy*, vol. 8, no. 4, pp. 807–817, 2024. DOI: 10.1017/bpp.2024.7.

[15] T. Grüne-Yanoff and R. Hertwig, "Nudge versus boost: How coherent are policy and theory?" *Minds and Machines*, vol. 26, no. 2, pp. 149–183, 2016. DOI: 10.1007/s11023-015-9367-9.

[16] E. J. Johnson et al., "Beyond nudges: Tools of a choice architecture," *Marketing Letters*, vol. 23, no. 2, pp. 487–504, 2012. DOI: 10.1007/s11002-012-9186-1.

[17] S. Hess, A. Daly, and R. Batley, "Revisiting consistency with random utility maximisation: Theory and implications for practical work," *Theory and Decision*, vol. 84, no. 2, pp. 181–204, 2018. DOI: 10.1007/s11238-017-9651-7.

[18] D. Naous and C. Legner, "Leveraging market research techniques in is: A review and framework of conjoint analysis studies in the is discipline," *Communications of the Association for Information Systems*, vol. 49, 2021. DOI: 10.17705/1CAIS.04906.

[19] Z. R. Gabidullina, "The problem of projecting the origin of euclidean space onto the convex polyhedron," *Lobachevskii Journal of Mathematics*, vol. 39, no. 1, pp. 35–45, 2018. DOI: 10.1134/S1995080218010110.

[20] M. S. Spektor, S. Bhatia, and S. Gluth, "The elusiveness of context effects in decision making," *Trends in Cognitive Sciences*, vol. 25, no. 10, pp. 843–854, 2021. DOI: 10.1016/j.tics.2021.07.011.

[21] J. Więckowski and W. Sałabun, "Sensitivity analysis approaches in multi-criteria decision analysis: A systematic review," *Applied Soft Computing*, vol. 148, p. 110 915, 2023. DOI: 10.1016/j.asoc.2023.110915.

[22] G. Demir, P. Chatterjee, and D. Pamucar, "Sensitivity analysis in multi-criteria decision making: A state-of-the-art research perspective using bibliometric analysis," *Expert Systems with Applications*, vol. 237, p. 121 660, 2024. DOI: 10.1016/j.eswa.2023.121660.

[23] H. H. Bauschke and P. L. Combettes, *Convex Analysis and Monotone Operator Theory in Hilbert Spaces*, 2nd ed. Springer, 2017. DOI: 10.1007/978-3-319-48311-5.

[24] M. Weinmann, C. Schneider, and J. vom Brocke, "Digital nudging," *Business & Information Systems Engineering*, vol. 58, no. 6, pp. 433–436, 2016. DOI: 10.1007/s12599-016-0453-1.

[25] K. Ramakrishnan, "The influence of decoy pricing on consumer decision-making: A comprehensive analysis," *International Journal of Computer Engineering and Technology*, vol. 16, no. 1, pp. 138–150, 2025. DOI: 10.34218/ijcet_16_01_013.