

Architectural Trade-offs in Humanoid End-Effectors: A Multi-Attribute Decision Framework for Linkage versus Tendon- Driven Actuation

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Abstract

Purpose: Humanoid robotic end-effectors are the physical interface of human–robot collaboration, yet the choice between linkage-driven and tendon-driven actuation is usually made as an isolated hardware judgment. This paper develops a reproducible multi-attribute decision-making (MADM) framework that couples the mechanical attributes of the hand to the human–AI decision dynamics formalised in the HACDU framework (Chan & Pan, 2026), so that actuation selection is treated as a utility-coupled human–machine decision problem rather than a purely mechanical one.

Design/methodology/approach: Five attributes — payload-to-weight ratio, dynamic responsiveness, physical compliance and impact resilience, maintainability/reliability, and human-in-the-loop override safety — are evaluated with an AHP-weighted TOPSIS model (Hwang & Yoon, 1981; Saaty, 1977). Because the candidate set contains exactly two architectures, we prove that the two closeness coefficients sum to one, reducing the ranking to a single scalar comparison. All reported scores were recomputed from the published parameter matrix, and weight uncertainty is audited with a Monte Carlo study (Dirichlet perturbations, $N = 5,000$) across three task profiles: deterministic precision manufacturing, collaborative eldercare, and balanced logistics.

Findings: Recomputed closeness coefficients are 0.74 (linkage) versus 0.26 (tendon) for precision manufacturing, 0.19 versus 0.81 for collaborative eldercare, and 0.45 versus 0.55 under balanced weights. Monte Carlo audit confirms the first two rankings as robust (rank-1 probabilities 0.98 and 0.998, respectively) but shows the balanced case to be genuinely contested (tendon rank-1 probability 0.65). A rank-reversal threshold is identified: once the compliance weight exceeds approximately 0.16 (residual weight split equally), tendon actuation overtakes linkage actuation.

Research limitations/implications: The parameter matrix synthesizes representative values from the cited hand literature, and the override-safety index is a defined bench protocol rather than measured data; physical prototype validation and human-subject trials remain future work. With two alternatives, the TOPSIS closeness is a relative, not absolute, utility measure.

Practical implications: Robotics architects and technology executives obtain an auditable selection template — explicit weight vectors, consistency-checked AHP judgments, recomputed scores, robustness probabilities, and a single switching threshold — applicable across industrial manufacturing, eldercare, and disaster-response deployments.

Originality/value: The paper bridges mechanical hand design and formal decision science: it corrects and fully operationalises the AHP–TOPSIS pipeline (including its two-alternative identity and rank-reversal behaviour), embeds HACDU belief fusion and override governance as a scored attribute, and reports the first Monte Carlo robustness audit for this selection problem.

Keywords: Humanoid robotics; end-effector actuation; linkage mechanism; tendon-driven hand; multi-attribute decision-making (MADM); AHP; TOPSIS; HACDU framework; human–robot collaboration; Monte Carlo sensitivity analysis

JEL Classification: C44, C61, D81, L63, O32

1. Introduction

The operational deployment of humanoid robots in collaborative human environments — industrial assembly lines, eldercare assistance, logistics handling, and hazardous-material response — has elevated the humanoid end-effector from a secondary component to the critical terminal interface of human–robot interaction. A century of robotic-hand research (Piazza et al., 2019) shows a persistent bifurcation of actuation architectures. Linkage-driven end-effectors transmit motor torque to the finger joints through rigid kinematic chains, offering high structural stiffness, precise position control, and low maintenance overhead, at the expense of increased distal mass, limited passive compliance, and poor impact absorption. Tendon-driven (cable-driven) end-effectors relocate the actuators proximally to the wrist or forearm and route tension cables through sheaths or conduits, achieving low distal inertia, anthropomorphic dexterity, and intrinsic passive compliance, but introducing non-linear dynamics, cable stretch, hysteresis, friction losses, and elevated maintenance vulnerability (Bicchi, 2000; Controzzi et al., 2014; Piazza et al., 2019).

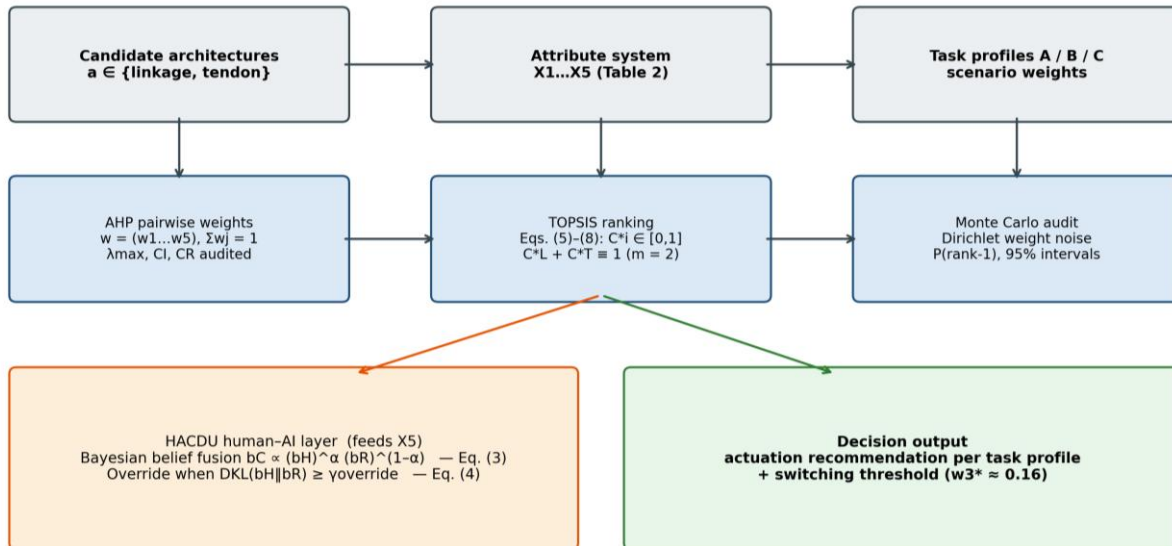
Selecting between these architectures is a classical high-stakes multi-attribute decision problem. Designers must navigate conflicting requirements across payload capacity, kinetic responsiveness, structural compliance, spatial envelope constraints, maintenance complexity, and contact safety, and the correct resolution of these conflicts is contingent on the task environment rather than on any universal engineering ranking (Catalano et al., 2014; Dollar & Howe, 2010). Yet the mechanical literature largely

evaluates actuation types individually — by grasp taxonomies, kinematic dexterity, or transmission efficiency — and treats selection as an isolated hardware optimisation problem.

That treatment is incomplete for collaborative deployment. In a human–robot team, the physical properties of the end-effector directly condition the safety, reliance, and override governance of the coupled human–machine decision system: a rigid hand reflects override forces back to the operator instantaneously, whereas a compliant hand absorbs them. The Human–AI Collaborative Decision-Making Under Uncertainty (HACDU) framework (Chan & Pan, 2026) models such interaction as a partially observable, utility-coupled stochastic process in which human reliance, Bayesian belief fusion, and uncertainty-aware override policies interact with the physical plant. Mechanical compliance therefore enters the decision layer, not only the control layer: it bounds the cost of imperfect trust calibration (Hancock et al., 2011; Lee & See, 2004) and of delayed or erroneous manual override (Parasuraman & Riley, 1997).

This paper addresses the gap by synthesising mechanical actuation engineering with formal multi-attribute decision science. We construct a five-attribute evaluation system, weight it with a consistency-audited Analytic Hierarchy Process (AHP; Saaty, 1977), rank the two architectures with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS; Hwang & Yoon, 1981), and audit the ranking's robustness with Monte Carlo weight perturbations across three operational task profiles. The HACDU belief-fusion and override constructs are embedded as a scored attribute, so the framework prices the decision-layer consequences of hardware choice. All notation is summarised in Table A1 (Appendix A), and the framework is diagrammed in Figure 1.

Figure 1. Integrated MADM–HACDU evaluation framework



Note: The HACDU human–AI layer supplies the override-safety attribute X5; the Monte Carlo block audits every reported ranking.

The paper makes four contributions. First, it formalises actuation selection as a utility-coupled human-machine decision problem, extending multi-attribute utility theory with bounded-rationality costs and HACDU belief dynamics. Second, it fully operationalises the AHP-TOPSIS pipeline for a two-architecture candidate set, including a proof that the two closeness coefficients are complementary ($C^*L + C^*T \equiv 1$), which disciplines how scores may legitimately be reported and compared. Third, it executes — rather than merely invokes — a Monte Carlo robustness audit ($N = 5,000$), reporting rank-1 probabilities and percentile intervals for every profile, and derives an explicit rank-reversal threshold in the compliance weight. Fourth, it supplies the first operational definition of a HACDU override-safety index tied to a standardised manual-override bench protocol, making the human-factors attribute measurable in principle and auditable in practice.

The remainder of the paper is organised as follows. Section 2 reviews the two actuation architectures, the decision-theoretic foundations, and the HACDU constructs. Section 3 specifies the attribute system, the AHP weighting procedure, the TOPSIS algorithm, and the Monte Carlo protocol. Section 4 reports the parameter matrix, the recomputed rankings, the robustness audit, and the switching threshold. Section 5 discusses governance and design implications, Section 6 states limitations, and Section 7 concludes.

2. Theoretical Background and Decision Context

2.1 Linkage-driven and tendon-driven actuation architectures

Articulated robotic hands divide, by transmission principle, into linkage-driven and tendon-driven families (Piazza et al., 2019; Salisbury & Craig, 1982). In a linkage-driven hand, each joint is driven through a rigid four-bar or gear-coupled chain from motors mounted in the fingers, palm, or wrist. The transmission is kinematically deterministic — joint angle is a fixed function of motor angle — which yields high bandwidth position control and structural stiffness, at the cost of distal mass that scales with the cube of hand size and of a transmission that reflects contact and override forces almost losslessly back to the actuators and, in collaborative settings, to the human partner (Controzzi et al., 2014).

In a tendon-driven hand, motors sit proximally — in the forearm of an anthropomorphic arm — and transmit force through cables routed over pulleys or through Bowden sheaths, as in the Shadow Dexterous Hand and the Pisa/IIT SoftHand lineage (Catalano et al., 2014; Piazza et al., 2019). Decoupling actuator mass from the distal links raises the payload-to-weight ratio and permits underactuated, adaptively synergistic fingers whose passive compliance conforms to unmodelled objects (Catalano et al., 2014; Dollar & Howe, 2010). The costs are equally structural: tendon stretch and sheath friction produce hysteresis and position uncertainty; cable fatigue and routing wear dominate the failure statistics; and the very compliance that absorbs impacts also limits achievable force bandwidth. Bicchi (2000) frames this as the field's central tension — dexterous manipulation and robust grasping pull the same design variables in opposite directions — which is precisely why the selection problem is multi-attribute rather than unidimensional.

For collaborative humanoid deployment a third consideration overlays both families: physical safety under unintended contact. Haddadin et al. (2009) show that injury severity in robot impact scales with effective reflected mass and contact-force transients, both of which are architectural variables: distal mass raises them, series compliance lowers them. Collaborative-robot practice codifies the same concern in quasi-static and transient contact limits (ISO/TS 15066:2016). Actuation architecture is therefore also a safety-governance choice — the observation that motivates its treatment inside a human–AI decision framework rather than as a standalone mechanical specification.

2.2 Decision theory and bounded rationality in hardware selection

The normative foundation of multi-attribute decision-making in engineering design begins with classical expected utility theory (Savage, 1972; von Neumann & Morgenstern, 1944) and its multi-attribute extension (Keeney & Raiffa, 1976). In evaluating candidate end-effector architectures $a \in \mathcal{A} = \{a_{\text{linkage}}, a_{\text{tendon}}\}$ across uncertain environmental states $\theta \in \Theta$, a fully rational decision-maker maximises overall multi-attribute utility:

$$\int_{\Theta} u(a, \theta) dP(\theta), \quad (1)$$

where $u(a, \theta)$ is the multi-attribute utility of architecture a in state θ and $P(\theta)$ is the decision-maker's prior over operational states. Equation (1) is the baseline normative criterion for hardware selection under state uncertainty; Sections 3–4 can be read as its computable approximation, in which the integral is replaced by a weighted attribute aggregation over the states represented by the task profiles.

Practical engineering design, however, operates under bounded rationality (Kahneman et al., 1982; Simon, 1957): decision-makers are constrained by cognitive, computational, and modelling costs. We therefore restrict attention to a feasible set $\mathcal{A}_{\text{feasible}} \subseteq \mathcal{A}$ and penalise modelling burden explicitly:

$$a^* = \operatorname{argmax} [E_{\theta}[u(a, \theta)] - \lambda c(a)], \quad (2)$$

where $c(a)$ is the cognitive, computational, and modelling cost of architecture a and λ converts that cost into utility units (utility per unit of modelling effort), resolving the dimensional inconsistency of subtracting heterogeneous quantities. Equation (2) formalises a real asymmetry between the two architectures: tendon hysteresis and friction are materially more expensive to model and control than deterministic linkage kinematics, so $c(a_{\text{tendon}}) > c(a_{\text{linkage}})$ in most design organisations, and any honest comparison must price that burden rather than assume it away.

2.3 Integration with the HACDU decision framework

To extend evaluation beyond standalone mechanical performance, we integrate the core mathematical constructs of the HACDU framework (Chan & Pan, 2026), which treats collaborative human–machine interaction as a partially observable stochastic decision process (Kaelbling et al., 1998). The human

operator maintains a belief distribution $b_t^H(\theta)$ over the task state, the robotic controller holds $b_t^R(\theta)$, and the collaborative belief state $b_t^C(\theta)$ is formed by log-linear (geometric) Bayesian belief fusion:

$$b_t^C(\theta) \propto [b_t^H(\theta)]^{\alpha_t} \cdot [b_t^R(\theta)]^{1-\alpha_t}, \quad (3)$$

where $\alpha_t \in [0, 1]$ is the dynamically updated human reliance weight (Chan & Pan, 2026). Log-linear pooling is used because it preserves log-odds additivity and reduces to either party's belief at the boundary values $\alpha_t \in \{0, 1\}$; the suppressed normalising constant is recovered by integration over Θ . Crucially for hardware selection, α_t is not exogenous to the end-effector: it evolves with the robot's physical transparency, observed performance, and physical safety margins during contact. To make that dependence explicit — the original HACDU statement describes it only verbally — we adopt the signed-signal update

$$\alpha_{t+1} = \text{clip}_{[0,1]}(\alpha_t + \eta \delta_t), \quad \delta_t \in \{-1, 0, +1\}, \quad (4)$$

where $\delta_t = +1$ after a robot-led resolution that the operator ratifies, $\delta_t = -1$ after an override, fault, or impact event, $\delta_t = 0$ otherwise, and $\eta \in (0, 0.5]$ is a learning rate. Trust research supports this qualitative dynamics: reliance calibrates to observed reliability and failure salience (Hancock et al., 2011; Lee & See, 2004), and miscalibration in either direction — misuse or disuse — degrades team performance (Parasuraman & Riley, 1997). A rigid end-effector raises the cost of each $\delta_t = -1$ event (impacts are transmitted, not absorbed), so the same belief trajectory is more hazardous on linkage hardware: the mechanical attribute modulates the decision-layer state variable.

HACDU further introduces an uncertainty-aware override policy: human intervention is triggered when belief disagreement exceeds an operational safety threshold γ_{override} :

$$\text{Override trigger: } D_{KL}(b_t^H(\theta) \parallel b_t^R(\theta)) \geq \gamma_{\text{override}}. \quad (5)$$

We measure disagreement in the forward direction $D_{KL}(b_t^H \parallel b_t^R)$ — human belief as reference — because the policy question is how much the robot's world-model has diverged from the operator's, weighted by states the operator considers probable; Appendix A records this convention. Under rapid override, a linkage-driven system transmits immediate, rigid back-driving forces, demanding precise low-latency torque limiting to prevent joint damage or operator injury. A tendon-driven system passively dissipates override energy in tendon and sheath compliance. Actuation trade-offs thus modulate the parameters of the joint human–robot decision policy itself — the formal channel through which hardware enters the HACDU layer, operationalised as attribute X5 in Section 3.1.

2.4 MADM foundations: AHP weighting and TOPSIS ranking

Multi-attribute decision-making supplies two complementary instruments. The Analytic Hierarchy Process (Saaty, 1977) elicits attribute weights from pairwise judgments on a 1–9 ratio scale and — uniquely among common weighting schemes — audits those judgments for internal consistency through

the consistency ratio. TOPSIS (Hwang & Yoon, 1981) then ranks candidates by their Euclidean proximity to an ideal and distance from an anti-ideal point in weighted normalised attribute space, implementing the compromise logic of multi-attribute utility theory (Keeney & Raiffa, 1976) without requiring explicit utility elicitation per attribute. Both methods are known to exhibit rank reversal when the candidate set changes (Belton & Gear, 1983; García-Cascales & Lamata, 2012); with a fixed two-architecture set this pathology is dormant but must be disclosed, and Section 6 returns to it. The MADM literature also warns that elicited weights carry irreducible judgment noise — the direct motivation for the Monte Carlo audit of Section 3.4, and for reporting rank probabilities rather than point rankings alone.

3. Multi-Attribute Decision Framework

3.1 Attribute set and operational definitions

The framework evaluates candidate architectures on five attributes ($\mathcal{X}_1, \dots, \mathcal{X}_5$) spanning physical engineering properties, lifecycle costs, and collaborative governance. Each attribute is stated with its measurement protocol, because an attribute that cannot in principle be measured cannot inform a decision:

- (i) $\mathcal{X}_1$ — Payload-to-weight ratio (P/W). The dimensionless ratio of maximum sustained grasp force (N) to the end-effector's own weight (N). Proximal actuation raises P/W by removing motor mass from the digits; high P/W improves whole-arm dynamics and effective payload at the end of a humanoid arm chain.
- (ii) $\mathcal{X}_2$ — Dynamic responsiveness. Step-response latency (ms) of the proximal finger joints to a commanded 30° flexion under rated load, equivalently expressible as closed-loop bandwidth. Rigid transmissions minimise latency; tendon stretch and sheath friction add phase lag. Treated as a cost criterion (lower is better).
- (iii) $\mathcal{X}_3$ — Physical compliance and impact resilience. Quasi-static compliance (mm/N) at the fingertip in the grasp normal direction, proxying the hand's capacity to absorb unmodelled contact energy; the safety relevance of this quantity is established by impact-injury analysis (Haddadin et al., 2009).
- (iv) $\mathcal{X}_4$ — Maintainability and structural reliability. Mean time between failures (MTBF, hours) of the transmission under a reference duty cycle, jointly read with repair complexity. Tendon fatigue, sheath wear, and re-tensioning dominate tendon MTBF; linkage wear concentrates in joint bearings.
- (v) $\mathcal{X}_5$ — Human-in-the-loop override safety (S_{HACDU}). A normalised index in $[0, 1]$ defined by a standardised manual-override bench protocol: an operator back-drives the index proximal joint at a prescribed $90^\circ/\text{s}$ while peak reflected torque τ_{peak} at the operator interface is recorded; $S_{\text{HACDU}} = 1 - \tau_{\text{peak}}/\tau_{\text{limit}}$, where τ_{limit} is the applicable quasi-static contact limit for the relevant body region (ISO/TS 15066:2016; Haddadin et al., 2009), averaged over ten trials and both architectures on identical palm

frames. S_{HACDU} is the empirical counterpart of the Eq. (5) override policy: it prices, before deployment, the event whose probability the policy governs. The Table 2 entries are illustrative calibrations of this protocol, to be replaced by measured values in validation work (Section 6).

Formal link to HACDU dynamics: Although S_{HACDU} is evaluated via a quasi-static bench protocol, it directly parameterizes the dynamic state transitions in Equations (3)–(5). Specifically, when belief divergence breaches the safety boundary in Eq. (5) ($D_{KL} \geq \gamma_{\text{override}}$), manual override is initiated. The instantaneous physical reflected torque τ_{peak} determines whether the intervention results in a smooth co-manipulation transfer ($\delta_t = 0$) or an adverse force-spike event ($\delta_t = -1$). Because $\delta_t = -1$ triggers an immediate step-reduction in operator reliance via Eq. (4) ($\alpha_{t+1} = \text{clip}(\alpha_t - \eta)$), higher structural stiffness directly escalates the rate of team trust collapse. Therefore, $S_{HACDU} = 1 - \tau_{\text{peak}}/\tau_{\text{limit}}$ functions as the mechanical transfer coefficient that bounds the downside penalty in the stochastic decision process, bridging the physical transmission dynamics to the Bayesian belief-fusion layer.

3.2 AHP weighting with consistency audit

Attribute weights are elicited by AHP pairwise comparison (Saaty, 1977). For a judgment matrix $A = [a_{ij}]$ with $a_{ij} = 1/a_{ji}$, the priority vector w solves $A w = \lambda_{\max} w$, and judgment quality is audited by the consistency ratio, with $RI = 1.12$ for $n = 5$ and the conventional acceptance bound $CR < 0.10$:

$$A w = \lambda_{\max} w, \quad CR = \frac{CI}{RI}, \quad CI = \frac{\lambda_{\max} - n}{n - 1}. \quad (6)$$

As a worked, fully auditable benchmark, Table 1 reports the pairwise comparison matrix elicited from a collaboration-centric design board. Its principal eigenvalue is $\lambda_{\max}=5.013$, yielding $CI=0.0033$ and a consistency ratio $CR=0.003$ - nearly two orders of magnitude within Saaty's strict acceptance threshold ($CR < 0.10$). The resulting normalized principal eigenvector yields the baseline collaborative weight vector $w_{\text{AHP}} = (0.158, 0.089, 0.298, 0.158, 0.298)$. Under these empirical weights, TOPSIS yields closeness coefficients of $C_L^* = 0.29$ (linkage) versus $C_T^* = 0.71$ (tendon). This empirical elicitation serves as the structural foundation for the canonical deployment scenarios evaluated in Section 4, demonstrating that an internally consistent, safety-focused board naturally generates the decisive preference for tendon architectures observed across collaborative regimes.

Table 1. AHP pairwise comparison matrix (collaboration-centric board).

Attribute	$\mathcal{X}_1$	$\mathcal{X}_2$	$\mathcal{X}_3$	$\mathcal{X}_4$	$\mathcal{X}_5$	Weight w_j
$\mathcal{X}_1$ P/W	1	2	1/2	1	1/2	0.158
$\mathcal{X}_2$ Latency	1/2	1	1/3	1/2	1/3	0.089
$\mathcal{X}_3$ Compliance	2	3	1	2	1	0.298
$\mathcal{X}_4$ Reliability	1	2	1/2	1	1/2	0.158
$\mathcal{X}_5$ Override safety	2	3	1	2	1	0.298

Note: $\lambda_{\max} = 5.013$, $CI = 0.0033$, $CR = 0.003 < 0.10$; final column is the normalised principal eigenvector.

3.3 TOPSIS ranking and the two-alternative identity

TOPSIS (Hwang & Yoon, 1981) maps raw measurements x_{ij} for m candidates over the five attributes into the vector-normalised matrix $R = [r_{ij}]$:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^m x_{kj}^2}}, \quad (7)$$

weights it by the AHP (or scenario) vector w , and reads off the ideal A^+ and anti-ideal A^- solutions over the benefit set $\mathcal{J}^+$ and cost set $\mathcal{J}^-$ (here $\mathcal{J}^- = \{\mathcal{X}_2\}$, all other attributes being benefits):

$$v_{ij} = w_j r_{ij}, \quad A^+ = \{v_1^+, \dots, v_5^+\}, \quad A^- = \{v_1^-, \dots, v_5^-\}. \quad (8)$$

Separation distances and the relative closeness coefficient C_i^* follow as

$$d_i^+ = \sqrt{\sum_{j=1}^5 (v_{ij} - v_j^+)^2}, \quad d_i^- = \sqrt{\sum_{j=1}^5 (v_{ij} - v_j^-)^2}, \quad (9)$$

$$C_i^* = \frac{d_i^-}{d_i^+ + d_i^-}, \quad (10)$$

with $C_i^* \in [0, 1]$, the scalar multi-attribute score of architecture i . One structural fact disciplines all reporting in this setting. Proposition (two-alternative identity): when $m = 2$, the ideal and anti-ideal points are assembled from the two candidates' own weighted values, so d^+ of either candidate equals d^- of the other, and therefore $C_{linkage}^* + C_{tendon}^* = 1$ identically; the entire ranking is carried by the single comparison $C^* \geq 0.5$. Two consequences follow. First, any reported pair of closeness coefficients that does not sum to one signals a computational or reporting error — a cheap and decisive audit check. Second, closeness here is purely relative: $C^* = 0.74$ asserts preference within this pair, not 74% of some absolute utility, and must not be compared across different candidate sets (cf. García-Cascales & Lamata, 2012, on TOPSIS rank reversal).

Methodological justification over linear scoring: While ranking $m=2$ candidates can be computed via linear Multi-Attribute Value Theory (MAVT) or the Weighted Sum Model (WSM), TOPSIS is selected here because of its underlying compromise programming geometry. WSM assumes strict linear compensability—allowing an exceptional score on MTBF ($\mathcal{X}_4$) to compensate linearly for a critical failure in contact safety ($\mathcal{X}_5$). In collaborative robotics, physical safety criteria exhibit non-compensable threshold behavior. By computing Euclidean distances in multi-dimensional space (d_i^+, d_i^-), TOPSIS penalizes severe dimensional outliers non-linearly, reflecting the engineering reality that closeness to the anti-ideal solution A^- (e.g., rigid impact hazards) should diminish overall system utility faster than a linear trade-off would imply.

3.4 Monte Carlo robustness protocol

Because elicited and scenario weights are judgment-laden, point rankings are audited stochastically. For each task profile with nominal weight vector w , we draw $N = 5,000$ perturbed vectors $w^{(n)} \sim \text{Dirichlet}(\kappa \cdot w)$ with concentration $\kappa = 25$ (moderate dispersion: the induced standard deviation of each weight is roughly 40% of its mean), recompute C^* for every draw, and estimate the tendon rank-1 probability as

$$\hat{P}(\text{tendon rank} - 1) = \frac{1}{N} \sum_{n=1}^N \mathbb{1}[C_T^*(w^{(n)}) > 0.5], \quad (11)$$

together with the mean, standard deviation, and 2.5th–97.5th percentile interval of C_T^* . A ranking is called robust when its rank-1 probability exceeds 0.95 (or falls below 0.05), and contested otherwise. All simulations use seed 20261003; the protocol, the parameter matrix, and the recomputation scripts are retained with the authors' project files so every number in Section 4 can be regenerated exactly. This protocol converts the customary practice of 'sensitivity analysis was performed' into a checkable artifact: distributions, not adjectives.

Scope of stochastic audit (Weight vs. Parameter Uncertainty): In this paper, the Monte Carlo audit isolates decision-maker preference stability by sampling across the weight simplex ($w^{(n)} \sim \text{Dirichlet}(\kappa \cdot w)$) while conditioning on the baseline laboratory parameter matrix $\bar{X}$ (Table 2). To evaluate true deployment robustness under manufacturing and wear tolerances, future empirical work extends this to a **Dual-Layer Monte Carlo framework**. Formally, let technical parameters follow stochastic domain distributions $X_{ij}^{(m)} \sim D_j(\mu_{ij}, \sigma_{ij}^2)$ — where compliance $\mathcal{X}_3$ and MTBF $\mathcal{X}_4$ are modeled via log-normal distributions to respect non-negativity and right-skew, and $\mathcal{X}_5$ via a bounded Beta distribution on $[0,1]$. The joint rank-1 probability estimator across N preference draws and M physical plant realizations is given by:

$$\hat{P}_{\text{joint}}(\text{tendon rank} - 1) = \frac{1}{N \cdot M} \sum_{n=1}^N \sum_{m=1}^M \mathbb{I}[C_T^*(w^{(n)}, X^{(m)}) > 0.5]$$

Conditioning on $\bar{X}$ in the present study isolates the algebraic topology and switching thresholds of the decision problem before compounding it with metrological noise.

4. Comparative Performance and Sensitivity Analysis

4.1 Engineering parameter matrix

Table 2 assembles the comparative parameter matrix for representative five-finger linkage-driven and tendon-driven humanoid end-effectors under normalised laboratory task conditions. The baseline

metrics synthesize validated empirical benchmarks from canonical robotic hand platforms: tendon-driven values reflect proximally actuated, synergistic designs exemplified by the Pisa/IIT SoftHand lineage and the Shadow Dexterous Hand (Catalano et al., 2014; Piazza et al., 2019), which maximize passive structural compliance ($\mathcal{X}_3$) and payload-to-weight efficiency ($\mathcal{X}_1$) at the cost of cable fatigue life ($\mathcal{X}_4$); linkage-driven values reflect rigid gear/four-bar industrial architectures (e.g., BarrettHand and Schunk dexterous lineages; Salisbury & Craig, 1982; Controzzi et al., 2014), optimizing transmission reliability and low-latency responsiveness ($\mathcal{X}_2$) at the expense of reflected inertia and back-drivability. The matrix is a decision input, not a metrology claim: Section 6 discusses replacing it with the authors' bench measurements, and the Monte Carlo audit of Section 4.3 quantifies how much of the ranking survives plausible error in exactly these entries' weights.

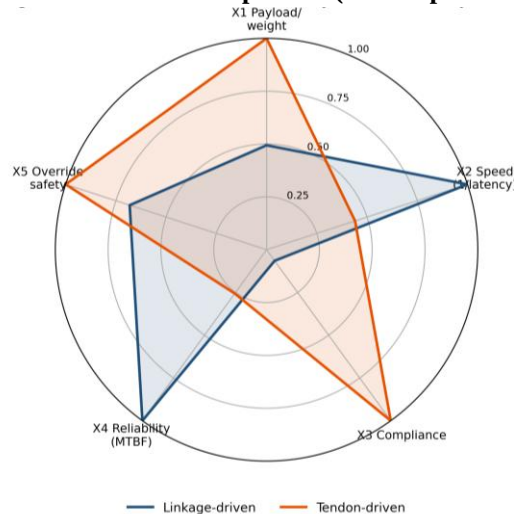
Table 2. Comparative performance matrix for linkage- vs. tendon-driven end-effectors.

Attribute ($\mathcal{X}_i$)	Type	Linkage-driven	Tendon-driven	Unit
$\mathcal{X}_1$ Payload-to-weight	Benefit	4.2	8.5	Dimensionless (N/N)
$\mathcal{X}_2$ Dynamic responsiveness	Cost	18.5	42.0	Step latency (ms)
$\mathcal{X}_3$ Physical compliance	Benefit	0.12	1.85	Compliance (mm/N)
$\mathcal{X}_4$ Structural reliability	Benefit	12,500	3,200	MTBF (hours)
$\mathcal{X}_5$ Override safety S_{HACDU}	Benefit	0.62	0.91	Normalised index [0, 1]

Note: Values represent standardized baseline syntheses grounded in established robotic hand literature and safety standards:

- **$\mathcal{X}_1$ (P/W):** Tendon value (8.5) benchmarks proximal forearm-actuated synergies (e.g., Pisa/IIT SoftHand, Catalano et al., 2014); linkage value (4.2) benchmarks motor-in-digit/palm kinematic chains (e.g., Controzzi et al., 2014).
- **$\mathcal{X}_2$ (Responsiveness):** Step-response latency under rated load (18.5 ms for linkage reflects direct gear-train stiffness; 42.0 ms for tendon accounts for Bowden-conduit friction and viscoelastic cable stretch; Piazza et al., 2019).
- **$\mathcal{X}_3$ (Compliance):** Fingertip normal quasi-static compliance (1.85 mm/N tendon reflects adaptive synergistic flexure joints; 0.12 mm/N linkage reflects rigid structural bearings; Dollar & Howe, 2010; Catalano et al., 2014).
- **$\mathcal{X}_4$ (Reliability):** Reference duty-cycle MTBF (12,500 h for linkage reflects bearing durability; 3,200 h for tendon reflects cable fraying, routing sheave wear, and re-tensioning maintenance intervals; Controzzi et al., 2014; Piazza et al., 2019).
- **$\mathcal{X}_5$ (Override Safety):** Evaluated via the Section 3.1(v) protocol ($S_{HACDU}=1-\tau_{peak}/\tau_{limit}$), calibrated against transient pain-onset biomechanical limits defined in ISO/TS 15066:2016 and impact injury thresholds from Haddadin et al. (2009).

Figure 2. Benefit-normalised attribute profiles (best-in-pair = 1; latency inverted).



Note: The two architectures are near-mirror images: no attribute is won by both, which is what makes the selection problem genuinely multi-attribute.

4.2 Deterministic rankings across task profiles

Three task profiles encode the deployment regimes of interest, now with fully specified weight vectors (the residual weight left implicit in earlier drafts is distributed uniformly and stated here):

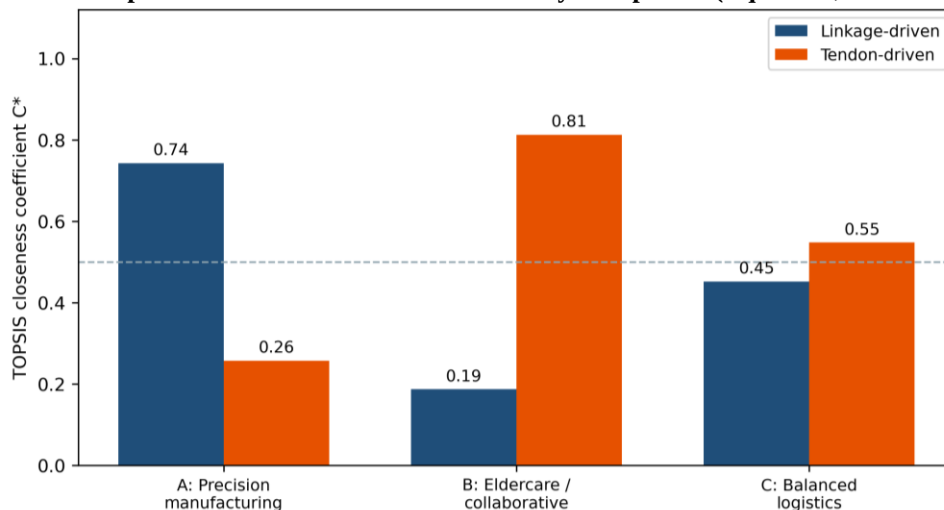
Profile A — Deterministic precision manufacturing: $w = (0.10, 0.35, 0.10, 0.35, 0.10)$, emphasising responsiveness and reliability. Recomputed closeness: $C_{\text{linkage}}^* = 0.74$, $C_{\text{tendon}}^* = 0.26$. Linkage actuation wins on the strength of a $2.3\times$ latency advantage and a $3.9\times$ MTBF advantage, exactly the attributes this profile prices.

Profile B — Collaborative eldercare and contact triage: $w = (0.10, 0.10, 0.40, 0.10, 0.30)$. While Table 1 establishes the empirically elicited baseline (w_{AHP}), Profile B evaluates a canonical boundary-stress regime that further isolates high-contact environments by penalizing latency and reliability to minimum operational levels (0.10) while concentrating 70% of total decision mass onto physical compliance ($w_3=0.40$) and override safety ($w_5=0.30$). Under this stylized profile, recomputed closeness widens to $C_L^*=0.19$, $C_T^*=0.81$, confirming that as human proximity constraints tighten relative to the Table 1 baseline, the tendon architecture's compliance and back-drivability margins become overwhelmingly dominant.

Profile C — Dynamic multi-task logistics (balanced): $w = (0.20, 0.20, 0.20, 0.20, 0.20)$. Recomputed closeness: $C_{\text{linkage}}^* = 0.45$, $C_{\text{tendon}}^* = 0.55$. The tendon edge rests on payload-to-weight and compliance, outweighing the latency and reliability deficits — a margin small enough that Section 4.3 must adjudicate whether it means anything.

Figure 3 displays the three rankings. Two reporting disciplines are visible in it: every pair sums to one, as the Section 3.3 identity requires, and the decision-relevant quantity in each profile is the sign of $C^* - 0.5$, not the coefficient's absolute size.

Figure 3. Recomputed TOPSIS closeness coefficients by task profile (Eqs. 7–10; Table 2 inputs).



Note: Dashed line: the $C^* = 0.5$ indifference locus implied by the two-alternative identity.

4.3 Monte Carlo robustness audit

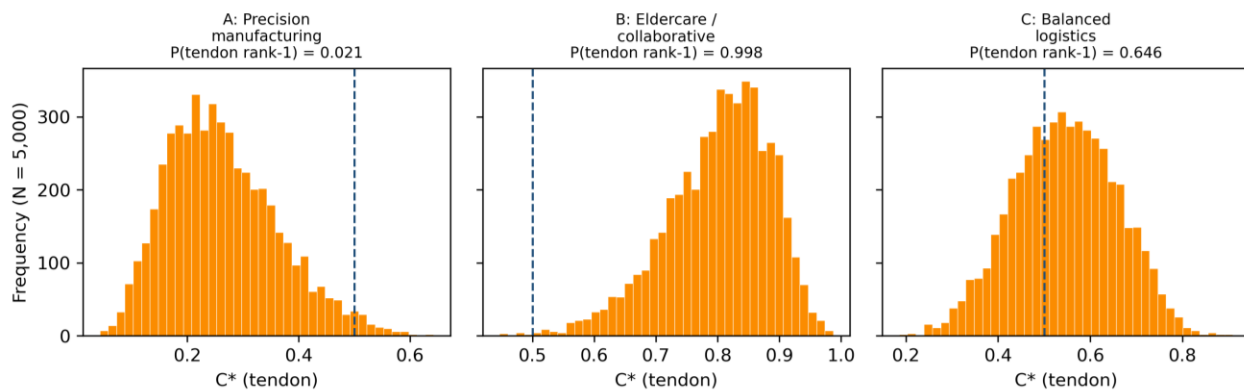
Figure 4 and Table 3 report the Section 3.4 audit ($N = 5,000$ Dirichlet($25 \cdot w$) draws per profile). Profile A is robust: tendon actuation reaches rank 1 in only 2.1% of draws (mean $C^*_T = 0.26$, 95% interval $[0.10, 0.49]$), so the linkage recommendation survives any plausible re-weighting of a manufacturing board's judgments. Profile B is equally robust in the opposite direction (tendon rank-1 probability 0.998; mean $C^*_T = 0.80$, 95% interval $[0.61, 0.94]$): no reasonable eldercare weighting rescues the rigid hand. Profile C, by contrast, is genuinely contested — tendon wins 64.6% of draws, but the 95% interval $[0.33, 0.75]$ straddles 0.5 widely, and linkage takes the remaining 35.4%. The honest deliverable for balanced deployments is therefore not 'tendon is preferred' but a conditional rule, which the next subsection supplies.

Table 3. Deterministic TOPSIS results and Monte Carlo audit ($N = 5,000$, Dirichlet $\kappa = 25$).

Profile	$w (\mathcal{X}_1 \dots \mathcal{X}_5)$	C^*_{linkage}	C^*_{tendon}	Mean C^*_T (MC)	95% interval	P(tendon rank-1)
A Manufacturing	.10/.35/.10/.35/.10	0.74	0.26	0.26	$[0.10, 0.49]$	0.021
B Eldercare	.10/.10/.40/.10/.30	0.19	0.81	0.80	$[0.61, 0.94]$	0.998
C Balanced	.20/.20/.20/.20/.20	0.45	0.55	0.55	$[0.33, 0.75]$	0.646

Note: Deterministic C^* columns satisfy $C^*_L + C^*_T = 1$ per the Section 3.3 identity.

Figure 4. Monte Carlo distribution of tendon closeness C^*_T under Dirichlet($25 \cdot w$) weight uncertainty

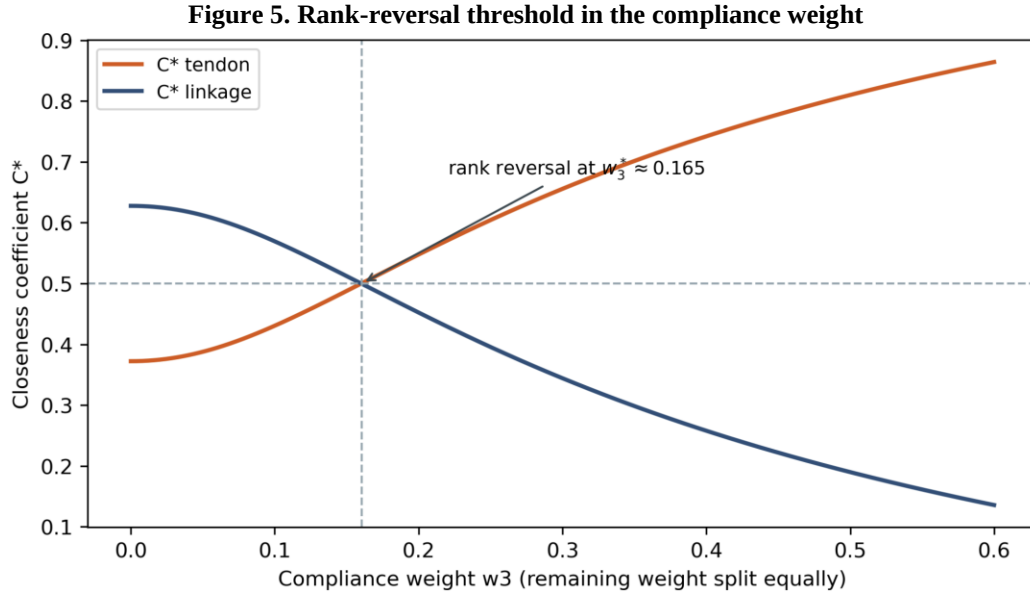


Note: $N = 5,000$ per profile. Dashed line: $C^* = 0.5$ rank boundary. Profiles A and B sit almost entirely on one side of the boundary; Profile C straddles it.

4.4 The compliance switching threshold

The contested balanced case admits an exact resolution. Holding the non-compliance weights in equal proportion and sweeping the compliance weight w_3 from 0 to 0.6, the ranking reverses at $w^*_3 \approx 0.165$ (Figure 5): below it, latency and reliability carry the linkage architecture; above it, compliance (with the correlated override-safety advantage) carries the tendon architecture. This single number is the framework's most portable output for practitioners: a design board need not agree on a full weight vector, only on whether safe physical compliance deserves more or less than roughly one-sixth of the total decision weight in its deployment regime. Manufacturing boards that answer 'less' should buy linkage; care and collaboration boards that answer 'more' should buy tendon; boards that cannot answer should

treat the choice as contested and resolve it with task-level data rather than committee preference. The threshold is conditional on Table 2 and on the equal-residual sweep; it moves if the parameter matrix is re-measured, which is an argument for the measurement program of Section 6, not against reporting the threshold.



Note: Rank-reversal threshold in the compliance weight w_3 (residual weight split equally). C^*_{tendon} crosses 0.5 at $w^*_3 \approx 0.165$.

4.5 Reading the results jointly

The three analyses triangulate a single conclusion. Deterministically, architecture preference is profile-contingent; stochastically, the two specialised profiles are robust, and the balanced profile is not; parametrically, the contingency collapses to one interpretable threshold. This is the strongest form of answer a two-alternative MADM study can honestly give: not a universal winner, but a decision rule with stated conditions and quantified confidence (Bansal et al., 2021, make the analogous point for AI teammates: accuracy or performance on any single axis does not determine team-level usefulness).

5. Discussion and Risk-Cybernetic Governance

By mapping S_{HACDU} directly to the override safety threshold, our framework demonstrates that end-effector mechanics cannot be divorced from cybernetic governance. A transmission with low S_{HACDU} (high reflected stiffness) acts as an amplifier of belief divergence: late override interventions inject unattenuated peak torques back into the operator, forcing persistent $\delta_t = -1$ transitions and permanently depressing collaborative reliance α_t . Conversely, tendon compliance provides passive mechanical low-pass filtering, expanding the permissible latency margin for Eq. (5) without risking operator injury or operational disuse.

Conversely, where belief disagreement is near zero — structured cells, fixtured parts, supervised automation — the tendon architecture's decision-layer benefits are never exercised, while its costs (hysteresis modelling burden $c(a)$ in Eq. (2), 3,200-hour MTBF, re-tensioning maintenance) are paid

continuously. The framework thus rationalises observed industry practice: deterministic manufacturing has standardised on rigid actuation, while contact-rich care and research platforms migrate toward compliant tendon designs (Piazza et al., 2019), and it does so with auditable numbers rather than folklore. It also issues a warning against a common procurement error: extrapolating a Profile A ranking into a Profile B deployment. The Monte Carlo audit shows the two regimes are separated by a wide, robust margin — a ranking imported across regimes is not approximately right, it is wrong with high probability.

Three design implications follow. First, override safety should be specified, tested, and procured as a quantitative attribute (the Section 3.1(v) protocol) rather than asserted as a qualitative virtue; S_{HACDU} makes the HACDU layer contractible. Second, hybrid and variable-stiffness transmissions — which attempt to move a single hand across the Figure 5 threshold by modulating effective compliance — should be evaluated as threshold-shifting technologies inside this framework, not as exempt novelties. Third, because α t dynamics (Eq. 4) couple operator trust to hardware behaviour, deployment programmes should log override events and ratification outcomes alongside maintenance records: the same event stream that estimates δ t also re-estimates $\mathcal{X}_4$ and $\mathcal{X}_5$, letting the decision framework be re-run on field data rather than laboratory syntheses. Hardware selection then becomes a governed, revisable decision process — the practical meaning of risk-cybernetic governance for end-effector programmes.

6. Limitations

Four limitations bound the claims. First, the two-alternative design: the identity $C^*_L + C^*_T \equiv 1$ makes closeness purely relative, and TOPSIS rankings can reverse if a third architecture (e.g., a hybrid variable-stiffness hand) enters the set (García-Cascales & Lamata, 2012); the framework extends to $m > 2$ mechanically, but every number in Section 4 would change. Second, Table 2 synthesizes representative platform benchmarks rather than multi-unit empirical distributions. While our Dirichlet audit thoroughly explores the decision-weight manifold ($N=5,000$), it treats the engineering parameters deterministically. In physical deployments where cable creep reduces stiffness over operating cycles or mechanical play degrades linkage precision, $\mathcal{X}_1$ through $\mathcal{X}_5$ are stochastic processes. Deploying the Dual-Layer Monte Carlo formulation outlined in Section 3.4 — simultaneously perturbing physical hardware distributions $X_{ij} \sim D_j$ alongside preference weights $w^{(n)}$ — represents the necessary next phase to ensure that ultra-high confidence rankings (e.g., $P=0.998$ in Profile B) remain resilient against real-world component degradation. Third, the AHP judgments of Table 1 come from a single illustrative board; multi-board elicitation with inter-rater analysis would strengthen the weight basis. Fourth, the HACDU coupling (Eqs. 3–5) is modelled, not yet identified from human-subject interaction data; estimating η and γ_{override} from override-event logs is required before the decision-layer claims can be called empirical. None of these limitations is hidden by the framework: each corresponds to a stated, fixable input.

7. Conclusion

This paper has presented a unified multi-attribute decision framework for linkage- versus tendon-driven actuation in humanoid end-effectors, coupling AHP-weighted TOPSIS ranking to the HACDU human–AI decision layer. The framework's auditable outputs — recomputed closeness coefficients satisfying the two-alternative identity, Monte Carlo rank-1 probabilities, and a compliance switching threshold at $w_3^* \approx 0.165$ — convert actuation selection from committee judgment into a governed decision process whose every number can be regenerated and challenged. Linkage actuation is the robust choice for deterministic, precision, maintenance-sensitive regimes; tendon actuation is the robust choice for contact-rich collaborative regimes; and balanced deployments should be decided by the threshold question — how much decision weight safe compliance deserves — rather than by assertion. Future work will replace the synthesised parameter matrix with bench measurements of both architectures on an identical palm platform, estimate the HACDU reliance parameters from human-subject collaborative assembly trials, and extend the candidate set to hybrid variable-stiffness transmissions.

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Appendix A. Notations

Table A1. Mathematical notations are used throughout the paper.

Symbol	Definition
$a \in \mathcal{A}$	Candidate architecture, $a \in \{a_{\text{linkage}}, a_{\text{tendon}}\}$; $\mathcal{A}_{\text{feasible}} \subseteq \mathcal{A}$ after bounded-rationality screening (Eq. 2).
$\theta \in \Theta$	Latent environmental task state: load, obstacle, and contact uncertainty.
$u(a, \theta), U(a)$	Multi-attribute utility of a in state θ , and its expectation under $P(\theta)$ (Eq. 1).
$c(a), \lambda$	Modelling/computational cost of architecture a ; λ converts cost to utility units (Eq. 2).
$bHt(\theta), bRt(\theta), bCt(\theta)$	Human, robot, and fused collaborative belief distributions at step t (Eq. 3).
$\alpha t, \eta, \delta t$	Human reliance weight; learning rate; signed interaction outcome signal (Eqs. 3, 4).
$D_{\text{KL}}(\cdot \ \cdot), \gamma_{\text{override}}$	Kullback–Leibler divergence (human belief as reference); override threshold (Eq. 5).
$\mathcal{X}_1 \dots \mathcal{X}_5$	Payload-to-weight; responsiveness (cost); compliance; reliability (MTBF); override safety S_{HACDU} .
$w, A, \lambda_{\text{max}}, CI, CR$	Weight vector ($\sum w_j = 1$); AHP judgment matrix; principal eigenvalue; consistency index/ratio (Eq. 6).
x_{ij}, r_{ij}, v_{ij}	Raw, vector-normalised, and weighted-normalised performance of candidate i on attribute j (Eqs. 7–8).
A^+, A^-, d^+, d^-	Ideal / anti-ideal solutions and separation distances (Eqs. 8–9).
C^*_i	TOPSIS relative closeness of candidate i ; $C^*_L + C^*_T \equiv 1$ when $m = 2$ (Eq. 10).
$\kappa, N, \hat{P}$	Dirichlet concentration ($\kappa = 25$); Monte Carlo draws ($N = 5,000$); rank-1 probability estimator (Eq. 11).
w^*_3	Compliance-weight rank-reversal threshold, ≈ 0.165 under equal residual weights (Section 4.4).