

Temperament Engineering: Designing Strategic Behavioural Diversity in Robot Swarms

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Abstract

Behavioural heterogeneity is increasingly recognised as enabling robot swarm function, but lacks systematic design methods. In animal behaviour, ‘temperament’ denotes the consistent individual differences in behaviour that persist across time and context; I propose ‘temperament engineering’, a bio-inspired framework that treats the swarm’s distribution of temperaments, rather than the individual controller, as the design object. Drawing on a finite set of evolutionarily validated behavioural axes, it calibrates the swarm’s emergent adaptation to the mission ecology: risk against reward, novelty against familiarity, exertion against conservation.

Keywords: Swarm robotics, Behavioural heterogeneity, Animal temperament, Embodied intelligence, Bio-inspired design, Emergent collective behaviour, Mission ecology

No two robots are truly identical. Even with best-efforts manufacturing and calibration, ‘quasi-homogeneity’ [1, 2] is the best a swarm can attain, and the residual variation is usually treated as an imperfection to be minimised. In animal collectives the reverse holds: individual behavioural variation is shaped by evolution and often decisive for group performance [3–5]. Such heterogeneity is increasingly recognised as an enabler for swarm function — through uncalibrated ‘noise’ [6], role specialisation [7] or decision-rule diversity [8] — yet the field lacks a systematic way to engineer the behavioural variation most relevant to field deployment. Calibration, battery state, sensor drift and manufacturing tolerance inevitably produce variation in how robots

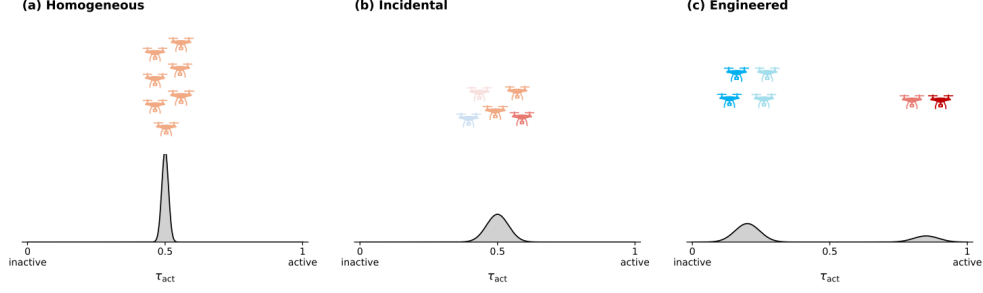


Fig. 1 (Quasi-)homogeneous, incidental, and engineered temperament distributions along the activity-level axis. Each panel shows a representative swarm of UAVs whose colour encodes $\tau_{\text{act}} \in [0, 1]$, from blue (inactive) to red (active), above the underlying distribution. (a) A (quasi-) homogeneous swarm with all robots calibrated at $\tau_{\text{act}} = 0.5$. (b) Incidental temperament: an approximately normal distribution arising from factors such as battery state, motor characteristics, lack of calibration and mechanical wear that the designer has not addressed. (c) Engineered temperament: a deliberately designed bimodal distribution comprising a sustained-patrol majority and a small burst-response minority, designed for a mission requiring both sustained coverage and rapid reaction. The comprehensive design process considers the full behavioural hypervolume across multiple relevant axes.

sense and act, with distributions typically approximately normal, reflecting their origin in many small independent physical sources [6]. Because sensing and actuation feed directly into behaviour, this physical variation manifests as behavioural variation — most directly on the activity axis, where motor characteristics and battery state set how fast and how far a robot moves, and indirectly on others, as when miscalibrated perception shifts the effective threshold at which a robot accepts risk. Along such axes the swarm already occupies a distribution of values rather than a single point. This is *incidental* temperament variation, the unintended distribution produced by embodied robot variation. Incidental variation does not populate every behavioural axis alike: the axes governing interaction between agents (such as sociability) are less exposed to physical happenstance, so variation there must be introduced by design rather than inherited from hardware. Across all axes alike — those where physical variation already impinges and those where it does not — I argue this variation should be deliberately shaped, not minimised or overlooked, and actively engineered for the mission ecology: the interaction of task demands, environmental conditions and operational hazards that determines which behavioural trade-offs a deployment turns on.

In animal behaviour research, ‘temperament’ (or ‘personality’) describes consistent individual differences in behaviour across time and contexts [3]. Although ‘personality’ is more common, and this nomenclature actively debated [9–12], I follow Réale et al. [3] in preferring ‘temperament’, which softens inferences about psychological disposition — doubly apt in robotics, where ‘personality’ risks connotations of intent or sentience. Their widely adopted framework distinguishes five axes — shyness–boldness, exploration–avoidance, activity level, aggressiveness and sociability [3] — which I consider below. Temperament is not task-level specialisation, which narrows an agent’s repertoire to a role; any embodied agent already sits somewhere on each trade-off axis,

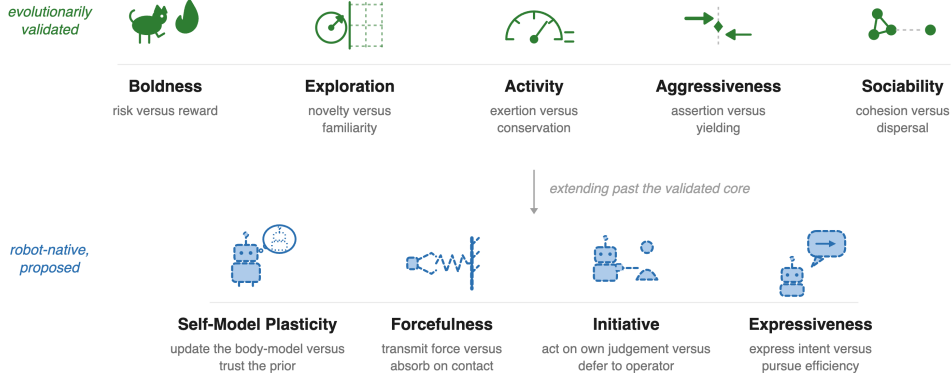


Fig. 2 The evolutionarily validated temperament axes (top) and some tentative robot-native axes (bottom). The five foundational axes are evolutionarily validated in animal collectives and proposed here as a design vocabulary for robot swarms. Three respects in which robots differ from animals open further, robot-native dimensions. First, a robot’s body is designed and explicitly modelled, so the model can be wrong and revised: this points toward *Self-Model Plasticity*, a readiness to update the internal dynamics-model rather than hold to the prior. Second, a robot’s body is not self-maintaining, and may absorb impact, reconfigure or be expended: this points toward *Forcefulness*, trading precision and force transmission against energy absorption and safety on contact — distinct from aggressiveness, which governs competition for resources rather than physical contact. Third, a robot operates under human supervision, which opens two distinct dimensions: *Initiative*, how far a robot acts on its own judgement rather than deferring to the operator; and *Expressiveness*, how far it shapes its behaviour to express intent and be legible to teammates and overseers, rather than pursuing raw efficiency. These robot-native axes are preliminary and non-exhaustive.

whether or not the designer has chosen where. The designer’s choice is therefore not whether to give a robot a temperament, but whether to design it deliberately or leave it an unintended consequence of controller and morphology (Figure 1). Rather than reinvent a vocabulary, I import a finite set of trade-off axes that natural selection has already validated (Figure 2, top) and recast it as an engineering design vocabulary; in the Outlook I tentatively suggest some axes unique to robotics (Figure 2, bottom).

Field robotics faces many of the challenges that shaped temperament in animals, and in embodied intelligence adaptive behaviour arises from the interaction of control, morphology and environment [13, 14]. A temperament’s substrate need not lie entirely in software: a compliant, energy-absorbing body [13, 15] inhabits a cost landscape favouring shy-typical behaviour, while a rigid, armoured platform shifts it toward boldness, with the integrity to act on risks a fragile platform could not survive. The coupling is loose: in birds, morphological–physiological integration is tight but body–behaviour coupling heterogeneous [16], and engineers may recombine morphology and behaviour more freely than evolution does. Temperament is thus the behavioural counterpart to morphological design, and in heterogeneous platforms (e.g., [17, 18]) it is natural to align the two: a large, well-sensorised robot is costly to lose, so a cautious profile protects the investment, while a small, expendable one is the natural candidate for boldness. Morphology and temperament then jointly define a swarm’s functional diversity.

This split in substrate has a consequence for how temperament can be assigned. The embodied component — resident in morphology, calibration and mechanical state — is fixed at the moment of action: it can be designed in advance but not re-bodied on demand. The software-resident component, by contrast, is a control parameter that can in principle be set, or reset, at deployment time or later. Temperament is therefore only partly a property a robot carries; in its software-resident part it is also a distribution that can be re-derived when circumstances change, conditioned on which robots are present and where — a flexibility unavailable to organisms, whose temperament is wholly embodied.

Whether fixed or reassignable, what matters is the distribution: a swarm whose robots share an identical behavioural strategy may be well adapted to a narrow range of conditions but brittle when conditions vary. Mechanisms such as online response-threshold adaptation [19, 20] can introduce post-deployment heterogeneity within an otherwise homogeneous controller, but this variation is restricted to the parameters the controller exposes; temperament engineering operates above this level, treating the strategic axes of variation themselves as design variables. The behavioural diversity of biological collectives can be understood as an anticipatory adaptation to their ecology — and the swarm’s behavioural distribution is the property temperament engineering sets out to design deliberately.

The Temperament Engineering Workflow

Temperament engineering turns these insights into a structured design method for robot swarms. I identify three design activities — Trait Mapping, Distribution Planning, and Plasticity Tuning (how far, if at all, a robot adjusts its temperament as its circumstances change) — which together furnish an informed starting point for the temperament parameters and reaction norms of a deployed swarm (Figure 3, Panel 1). This phase is top-down: it fixes the relevant axes and supplies a prior on how their values might be distributed, narrowing the search space to something tractable. The verified distribution and reaction-norm parameters that emerge from Phase 2 are guided by this prior but not constrained to it — bottom-up refinement may steer the design away from the initial proposal — before deployment, where they interact with the mission ecology to produce emergent collective behaviour (Panel 3).

From mission to temperament

Trait Mapping is deliberately general: any deployment descends the same hierarchy — from mission success criteria, to composite traits, to operational behaviours, to the temperament axes that shape them (Figure 3). This inverts the hierarchy Réale et al. [3] use to relate temperament to biological fitness through behaviour, with mission success as the engineering analogue of fitness. For instance, ‘comprehensive contamination mapping with minimal robot loss’ yields composite traits ‘thorough coverage’ and ‘survivability’, whose operational behaviours — ‘enter elevated-radiation zones’, ‘investigate novel sensor anomalies’ — map onto the shyness–boldness and exploration–avoidance axes. The descent is rarely a clean tree: one composite trait may draw on several axes, and one axis may serve several traits, so identifying the right

Temperament Engineering Workflow

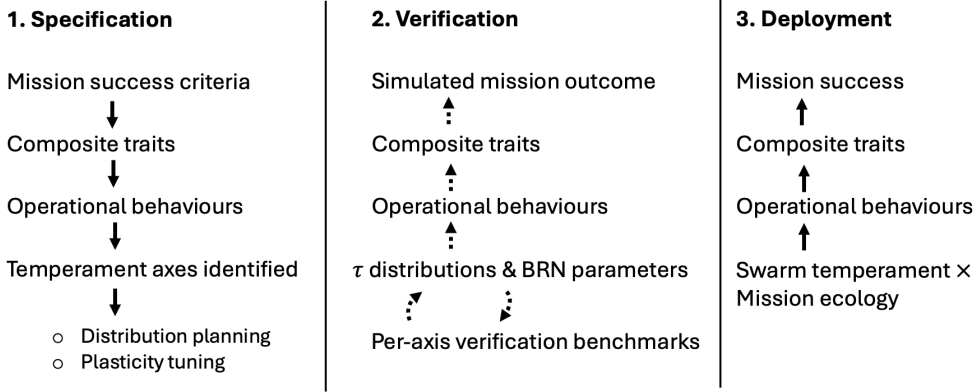


Fig. 3 The temperament engineering workflow comprises three phases. (1) **Specification (top-down)**: mission success criteria are decomposed downward through required composite traits and operational behaviours into an identified set of relevant temperament axes (trait mapping). The designer then proposes how the trait(s) are distributed across the swarm (distribution planning) and whether robots adjust their temperament in response to environmental cues via behavioural reaction norms (plasticity tuning, optional), furnishing a prior on the design. (2) **Verification**: this proposal seeds a bottom-up search — the proposed τ distributions and BRN parameters are refined and validated through increasingly integrated test scenarios, from per-axis calibration up to whole-mission rehearsal, where the realised spatial structure is checked against intent. The bottom loop indicates iterative parameter refinement, which may revise the proposal. (3) **Deployment**: the verified temperament parameters interact with the actual mission ecology to produce operational behaviours that determine mission success. The solid arrow style indicates the top-down prior (panel 1) and causal emergence (panel 3); the dashed, bottom-up refinement and verification (panel 2). The hierarchical structure is modelled after Réale et al. [3].

axes for a mission is a matter of judgement rather than mechanical decomposition. That judgement — anticipating which behavioural trade-offs a deployment will actually turn on — is where domain expertise enters the workflow, supplying the insightful prior the bottom-up search will later refine. Reasoning in temperament rather than bespoke task-specific parameters gives these system-level trade-offs a transferable, biologically grounded vocabulary that serves across very different deployments.

The remainder of this section develops the specification phase, which operates throughout on a single primitive: the temperament parameter τ and its reaction norm. Trait Mapping, above, identifies the relevant axes; Distribution Planning and Plasticity Tuning then shape τ across the swarm. Both presuppose the primitive on which they act, so I first make it precise — how each axis is rendered as a control parameter (*Defining the primitive*, below) — before turning to the two activities that distribute and tune it (*Shaping the distribution*).

Defining the primitive

Per-axis operationalisation

I propose that each temperament axis corresponds to a continuous modifier $\tau \in [0, 1]$ on the robot’s decision-making process. Each axis names a behavioural trade-off that field robots must resolve and that the behavioural-ecology literature has already characterised and validated; for each, I give the trade-off it captures and a representative control-theoretic operationalisation. The correspondences are illustrative rather than definitive.

- **Boldness** governs risk appetite: the willingness to act in the face of known hazard, such as entering zones of elevated danger. This is the domain of risk-aware planning and safety-critical control, where the question is not whether to avoid risk but how much to accept for a prospective reward [21, 22]. A scalar weight τ_{bold} trades known risk against potential reward. Following Réale et al. [3], this axis concerns response to *known* risk rather than novelty, which is captured separately by exploration–avoidance.
- **Exploration** governs novelty-seeking: investigating unfamiliar or unmapped regions versus exploiting the well-characterised. This is the exploration–exploitation trade-off in autonomous mapping and active perception, where information-theoretic controllers weigh expected information gain against the cost of leaving known, productive areas [23, 24]. A parameter τ_{exp} shifts an objective function from task-driven cost minimisation towards information gain.
- **Activity** governs exertion and its costs: the intensity of behaviour, from sustained low-tempo patrol to burst-mode rapid response, and the maintenance of a reserve workforce or distributed energy store [25, 26]. Beyond energy, high activity hastens mechanical wear and calibration drift — a robotic echo of the pace-of-life syndrome, in which a faster tempo accompanies faster ageing [27]. A parameter τ_{act} scales the maximum velocity bound or the control-effort penalty.
- **Aggressiveness** governs assertiveness in competition for shared resources — charging stations, bandwidth, contested space — concretely, how yielding is apportioned during path deconfliction [28]: an assertive robot claims right-of-way while a deferential one shoulders more of the avoidance responsibility [29, 30]. A parameter τ_{agg} modulates this priority, so that higher- τ_{agg} robots impose more of the burden on others.
- **Sociability** governs the tendency to aggregate or disperse: balancing spatial coverage against the proximity needed for local sensing and consensus. In communication-constrained swarms it shapes network topology — sociable ‘anchor’ robots holding a connected backbone while others range to the periphery [31, 32]. A parameter τ_{soc} scales the attractive component of an artificial potential field [33], or the target algebraic connectivity of the communication graph [34].

The mapping is many-to-many rather than one-to-one: a single mission requirement may load onto several axes (survivability draws on both shyness–boldness and activity level), and a single axis may serve several requirements. Its specific control-theoretic realisation depends on the deployment context, as the next section develops.

Controller-agnostic implementation

This vocabulary is illustrative, not prescriptive: the framework is agnostic to the robot’s control mechanism — the sense-decide-act architecture through which behaviour is computed — and applies wherever that behaviour can be modulated by a low-dimensional parameter. In behaviour-based or subsumption architectures [35], it adjusts module activation thresholds; in multi-agent reinforcement learning, the temperament vector conditions the policy [36], letting one network express different temperaments at inference; in planners built on large language or vision-language-action models [37, 38], it can be encoded in the system prompt or used to filter candidate plans. In each case the temperament parameter operates above the controller’s internal mechanism: it does not replace the controller but shapes the distribution of behaviours it produces. The top-down phase supplies a prior, not a fixed target: it fixes the axes and a plausible distribution over them, narrowing the search enough that any bottom-up method — such as evolutionary or learning-based, as swarm robotics commonly favours [39] — can search the remaining controller space efficiently. Such search sits naturally in the verification loop (Figure 3, Panel 2), seeded by the top-down proposal but free to settle on a distribution the prior did not anticipate. This is the off-line design programme for swarms, in which behaviour is optimised in simulation before deployment [40, 41]; there, expert-supplied template solutions can seed the search rather than be rediscovered each time — the role played here by the top-down prior.

This controller agnosticism is distinct from the question of how coordination authority is distributed across the collective: temperament engineering’s functional payoff is greatest under decentralisation, where a temperament distribution’s anticipatory adaptation to the mission ecology substitutes for the global adaptivity a central planner would otherwise supply. A system that switches between centralised and self-organised coordination (e.g., [42]) would accordingly carry a latent temperament distribution: masked while the planner dictates behaviour, and — in its software-resident part — reassigned or released when control is shed.

Explainability and human oversight. This level of abstraction has direct consequences for explainability and human-robot interaction. The internal workings of a deep policy network or a foundation model are typically opaque to operators, but a temperament vector is not: a single human-readable parameter such as “boldness = 0.2” specifies in advance how the robot will weigh risk against reward across the decisions it faces. An operator who cannot reason about the latent dynamics of a learned controller can nonetheless reason about — and adjust — its temperament, and can predict the qualitative shape of its behaviour from that adjustment alone. Given that perceived temperament has been shown to influence human trust and collaborative efficiency in HRI [43–45], this offers a principled bridge between increasingly capable but opaque control mechanisms and the human supervisors who must monitor and steer them.

Shaping the distribution

Distribution Planning

Once the relevant axes have been identified (Trait Mapping) and operationalised (above), and a control architecture chosen, Distribution Planning sketches out the shape of the τ distribution across the swarm on each axis. The behavioural hypervolume (the region a swarm occupies in the multi-dimensional space of temperament axes) gives a quantitative handle: a swarm spanning a larger region may be more functionally diverse and resilient. But the design lever is not only how much variation to introduce but what kind: Twu et al. [46] distinguish disparity (how different agents are, captured by the hypervolume) from complexity (how evenly they are spread). The two come apart — an engineered bimodal distribution is high-disparity but low-complexity, spanning a wide range at two clustered points (Figure 1c), whereas incidental temperament shows the inverse (Figure 1b) — and Distribution Planning chooses the kind of heterogeneity deliberately. As the field matures, recurring distributional motifs — a bimodal split of bold and cautious robots, say — may become part of a designer’s repertoire.

Plasticity via behavioural reaction norms

The behavioural reaction norm (BRN) formalism from behavioural ecology gives a precise vocabulary for plasticity [47–49]. It decomposes behaviour into an elevation — the baseline trait value set during Trait Mapping and Distribution Planning — and a slope, the rate at which the trait changes along an environmental gradient such as battery voltage, local density, perceived threat or calibration drift. Plasticity Tuning specifies the slope: a robot’s instantaneous parameter is $\tau(c) = \tau_0 + \beta(c - \bar{c})$, with τ_0 the elevation, β the slope, and c a cue centred on its expected value. The linear form is only first-order — β is the local slope of a more general $\tau(c) = g(c)$, which need not be linear, as nonlinear reaction norms are common in nature [50].

Plasticity tuning spans a static and a dynamic regime, and the dynamic regime admits two degrees. In the *static* regime ($\beta = 0$) the robot holds its assigned τ whatever it meets. Holding τ fixed is a legitimate design choice, not merely the absence of plasticity. Even where plasticity is available, the optimal slope is rarely maximal: it is bounded by the cost of plasticity itself [51, 52], and by the reliability of the cue c as a predictor of the conditions the agent must match — the less reliable the cue, the shallower the optimal reaction norm [53], and an over-steep response in a rapidly varying or noisy environment can lag or overshoot, actively degrading performance [54]. A fixed temperament can therefore be efficient where the environment varies little, changes faster than the swarm can sense and respond, or offers no dependable cue to act on.

In the *dynamic* regime ($\beta \neq 0$) temperament shifts with circumstance: in the first degree the reaction norm is fixed and the robot moves along it under sensor feedback — scaling activity down, say, as battery voltage drops, to conserve the quality of its contribution; in the second, the robot also revises the norm itself, updating elevation and slope from accumulated experience. This last is a form of meta-learning (e.g., [55]) — a robot that not only adapts, but adapts how it adapts.

These degrees have precedents in the narrower setting of task-allocation thresholds, which the reaction-norm formalism subsumes as one low-level realisation: Wu and Mathias show that a heterogeneous range of fixed thresholds enables specialisation while avoiding maladaptive sink states [56], and Kazakova et al. that swarms respecialise by forgetting reinforced thresholds when demand shifts [57] — a threshold analogue of revising the reaction norm itself. The sim-to-real gap [40, 58, 59] is a natural case for employing the meta-learning regime: on detecting that its dynamics model mismatches real feedback, a robot can default to a cautious, low-activity state — first-degree plasticity preserving its integrity — while it revises the reaction norm itself from the accumulating mismatch evidence. Here the mismatch concerns the robot’s own model rather than its environment, foreshadowing the self-model plasticity axis of the Outlook.

Spatial expression and verification

A temperament distribution does not sit statically over the swarm: it expresses itself through movement. Activity governs how far a robot ranges, sociability whether it aggregates or disperses, boldness and exploration which regions it enters — so the distribution planned above induces a spatial distribution of robots, and with it the interaction structure determining who communicates and cooperates with whom. This is the link movement ecology draws between behavioural type and the spatial and social structure a population generates [32, 60, 61]; and because emergent capability is a product of that structure, not the temperament distribution alone, the same composition deployed into different environmental geometries [62, 63] need not perform alike. The swarm’s spatial expression is therefore emergent and resists accurate top-down prediction, which makes it the proper object of Phase 2 (Figure 3): the verification scenarios, escalating to whole-mission rehearsal, simulate the realised spatial behaviour and confirm that it supports the intended functional outcomes before deployment.

From Individual Temperament to Collective Behaviour

The five axes the framework rests on are not an arbitrary choice but are drawn from a mature body of behavioural-ecology theory. Since the early 2000s, the study of consistent individual differences in animals has grown rapidly under the labels ‘temperament’, ‘personality’ and ‘behavioural syndromes’ [3, 64, 65], and such variation, once treated as statistical noise around an adaptive mean, is now recognised as ubiquitous, heritable and ecologically consequential [66]. The foundational framework of Réale et al. [3] distinguishes five axes (Figure 2), capturing fundamental trade-offs: safety versus opportunity, novelty versus familiarity, energy expenditure versus conservation, individual advantage versus group cohesion [64].

These traits have measurable fitness consequences maintained by ecological trade-offs: bolder fish suffer higher avian predation [67], bolder seabirds expand their foraging range and raise offspring growth [68], and a meta-analysis finds boldness buys reproductive success at a survival cost [69], while more broadly such differences shape population persistence and community dynamics [66]. They often covary as

‘behavioural syndromes’ — bold individuals also tending to be more aggressive and exploratory [64, 65] — but where biological syndromes arise from genetic linkage and hormonal constraint, engineers can decouple the axes deliberately, abstracting the advantages of natural variation while engineering out its maladaptive correlations.

At the collective level, a group’s temperament distribution matters not additively but emergently. A few highly exploratory fish can dictate the foraging routes of a whole shoal, heterogeneous groups often outperforming homogeneous ones [70, 71]; honeybee colonies hold a stable mix of fast-inaccurate and slow-accurate foragers as a bet-hedge raising nectar intake across flower qualities [72]. These illustrate ‘collective personality’, an emergent group-level phenotype not reducible to the average of individual ones [73–75]. The engineering counterpart is already visible: Kengyel et al. [76] find an evolved behaviourally heterogeneous swarm outperforming every homogeneous baseline on aggregation, with the best mixture distinctly non-trivial; on the exploration–avoidance axis, simulated multi-robot patrols show a negatively skewed distribution — mostly attentive robots, a single exploratory one — outperforming homogeneous swarms once individuals share what they find [77]. Piro et al. [78] find mixed exploratory–exploitative swarms winning in turbulent olfactory search, because a fixed distribution of types resists spatial signal correlations that defeat an individually-balanced strategy. These remain scattered, largely single-axis results; assembling them into a systematic, multi-axis account is what temperament engineering sets out to do.

The behavioural hypervolume gives a quantitative handle on this collective diversity: adapted from the n -dimensional niche concept in ecology [79–81], it has been used to quantify the multi-dimensional behavioural-trait diversity of animal populations [4], including the functional diversity of personality traits among conspecifics [82]. A swarm differs in that its variation is organised toward shared tasks, so capability is genuinely emergent: the value of any one behavioural type depends on the whole collective, and no single-robot controller optimisation can substitute for getting the distribution right — yet the mature, quantitative vocabulary behavioural ecology has built for this variation is one swarm robotics has yet to adopt, even as it grapples with how to compare collective behaviours [83].

Beyond Roles and Thresholds

The framework set out above takes up a recognised challenge, posed but not yet met: operationalising swarm heterogeneity, in both hardware and control, as something the designer specifies [7, 84]. A survey of the landscape reveals a conspicuous gap: recent reviews of bio-inspired swarm robotics, while systematically mapping collective behaviour onto coordination and cooperation problems, treat variation among individuals as a matter of emergent dynamics or optimiser tuning rather than something the designer specifies [85, 86]. Research on multi-robot heterogeneity has focused predominantly on morphological and functional role differentiation, or on algorithmic task allocation where robots are assigned to tasks based on capability or cost [87]. When behavioural variation is introduced, it typically takes the form of pre-specified roles or reactive threshold rules, without a unifying vocabulary for what kinds of behavioural

variation matter and why. Emergent task specialisation in homogeneous groups of robots [39] or response-threshold adaptation [19, 20] produces behavioural variation as a byproduct of task allocation, rather than as a designed property addressing ecological trade-offs. Temperament parameters operate at a level above task-acceptance thresholds and can coexist with them rather than replacing them.

This gap matters because many of the hardest problems of field deployment are, in the end, behavioural ones. Robots must trade known risk against potential reward, balance exploiting known information against exploring the unknown, calibrate exertion against its energetic and mechanical costs, and choose whether to cluster or spread out. These decisions define each robot’s behavioural strategy, and their distribution across the swarm shapes collective performance in ways no low-level controller optimisation can replace. The case for behavioural diversity of this kind has been made at the level of research programme by Ayanian [88], whose ‘Diversity-enhanced Autonomy in Robot Teams’ (DART) paradigm argues that a team should carry a complementary ensemble of control policies rather than a single policy optimised under one set of assumptions and deployed to every robot. Temperament engineering operationalises that programme, but relocates the diversity: it specifies which behavioural dimensions to vary, drawn from a validated vocabulary, and how to distribute them across the team, and it does so at the level of the temperament parameter τ rather than the policy, so that a swarm running one shared controller — or one shared learned policy conditioned on τ — can nonetheless carry an engineered behavioural distribution. Prorok et al. [89] considered heterogeneity of binary capability traits, drawing on the biodiversity literature [90] to specify capability distributions across the swarm’s tasks. I instead consider continuous, temperament-axis variation across the swarm, anticipating its ‘mission ecology’ in deployment rather than its task allocation — a behavioural-strategy framework that complements such capability-heterogeneity work. Constraint-based robot ecology offers a further contrast: Egerstedt and colleagues argue that survivability constraints shape robot behaviour over long deployments [91, 92]; temperament engineering shares that ecological intuition but operates at a different level, because constraint-based design optimises a single robot against its habitat whereas temperament engineering targets the emergent capability that arises when a distribution of strategies interacts among robots and their environment via self-organisation [93].

Illustrative Deployment Scenarios

Hazardous infrastructure inspection

In nuclear decommissioning, robots perform remote inspection in constrained, highly regulated environments [94]. The shy–bold axis maps to the probability of entering elevated-radiation zones. A ‘shy’ temperament can be guaranteed by a tight control barrier function (CBF, [22]) that physically bars the robot from zones above a radiation threshold, whatever its higher-level goals. A ‘bold’ scout runs a relaxed CBF, accepting higher known radiation than the shy threshold permits. The biological pattern of risk-taking minorities backed by a resilient cautious majority [70, 71] suggests bimodal boldness distributions here.

Long-term environmental monitoring

Sparse swarms operate over kilometre-scale environments where intermittent connectivity and energy scarcity, not acute hazard, dominate [31]. The mission ecology rewards a broad behavioural hypervolume held stable over long horizons. τ_{exp} governs how strongly each robot weights information gain against return-to-contact: low- τ_{exp} robots are persistent path-followers keeping regular rendezvous with base stations, high- τ_{exp} outriders bias toward unvisited regions — a coverage-versus-discovery bet-hedge like the honeybee forager mix [72]. A closed-loop reaction norm scaling τ_{exp} down as battery voltage falls lets an outrider retreat to conservative path-following before it strands itself.

Assisted search-and-rescue

In urban search-and-rescue, swarms can rapidly map interiors and assess structural hazards under acute time pressure [24, 95]. Unlike monitoring, this rewards a deliberately skewed distribution: temperament engineering gives a principled way to choose how many high-activity, high-boldness robots to commit under constraints on battery and collapse risk. A small high- τ_{bold} , high- τ_{act} minority pushes into structurally uncertain volumes to find survivors fast, while a cautious majority consolidates maps and holds relays. Because the threat map is built online and unreliable early on, this is exactly the case for the meta-learning regime above: robots update their reaction norms as evidence of instability accumulates.

Outlook

Temperament engineering treats the temperament distribution — not any single controller — as the design object, and the swarm’s emergent collective capability as the design target. The most consequential work, I suspect, will lie not in any single axis but in the structure of the temperament space itself. That space is not a set of independent ‘dials’: in nature the traits covary as syndromes [64], and in swarms, engineered interactions between boldness, exploration, activity and sociability may instead produce nonlinear performance effects, tunable to a mission rather than inherited as evolutionary legacy. Prorok et al. [89] showed that as trait-space diversity grows, the set of distributions realising a given target shrinks, so that optimal configurations become harder to find; the same should hold along behavioural axes, where richer spaces carry a design cost of their own, and near-optimal rather than optimal τ distributions may prove the practical target — a compromise swarm roboticists know well. This question — when, and how much, heterogeneity repays its cost — is beginning to receive formal treatment: within multi-agent reinforcement learning, Amir et al. [96] characterise the conditions under which behavioural diversity raises collective return, in broad cases reducing it to a tractable test on the reward structure. Temperament engineering poses the same problem one level up, axis by axis, where the design object is a distribution over validated behavioural trade-offs rather than a space of learned policies.

A further question is whether the axis set should stop at five (Figure 2). The five are retained here as a validated core: each names a trade-off that natural selection has faced and negotiated, which is what lends the vocabulary its authority. A robot inherits

all of them — the biological axes sit wholly inside the robotic case. But where the animal is solely an evolved body, the robot is also designed and modelled, disposable rather than self-maintaining, and answerable to a human operator. Each of these is a respect in which the robot extends beyond the animal, and each raises a trade-off the five do not reach.

Because a robot’s body is designed, and explicitly modelled, its self-model may be wrong, and may be revised: this invites a **‘Self-Model Plasticity’** axis, a readiness to revise the internal dynamics-model [97, 98] in the light of fresh sensorimotor evidence rather than hold to the prior — where exploration–avoidance concerns novelty in the world, this concerns novelty in the self. Because its body is not self-maintaining, and can be made to yield or reconfigure, how far it resists or gives way on contact becomes a behavioural setting in its own right: a **‘Forcefulness’** axis, trading precision and force transmission against energy absorption and safety on contact [99] — distinct from aggressiveness in governing physical engagement rather than resource competition. And because it acts within a human-authored command structure, two further dimensions arise. **‘Initiative’** fixes a robot’s position on the authority gradient [100], how far it acts on its own judgement rather than deferring to the operator: a gradient evolution never had to negotiate, and one distinct from the competition among peers that aggressiveness captures. **‘Expressiveness’** is the degree to which a robot shapes its behaviour to express its intent and remain legible to teammates and overseers [101], trading raw efficiency for inferability. The two are largely orthogonal — a robot may be deferential yet opaque, or high in initiative yet self-explaining — but they interact, because a supervisor can only sensibly grant autonomy to a robot whose behaviour it can predict; and perceived temperament is already known to influence operator trust [43–45]. Charting which of these dimensions are new, which extend a biological precedent, and which collide with one another is itself a programme worth pursuing.

Beyond enumerating axes, the framework’s value is that it makes calibration a well-posed problem. Because it operates above the controller, it is indifferent to the controller’s internals: low-level temperament parameters may override the unsafe plans of an otherwise-opaque foundation-model planner [102], acting as a kind of embodied safety filter. It identifies which behavioural dimensions warrant variation and how to distribute them, without yet prescribing where on each axis the τ distribution should sit or how reaction norms should be set. It turns that calibration from an ad hoc choice into a problem with a finite vocabulary of axes, a formalism for distributions and plasticity, and a clear design object. A first foothold already exists — engineered heterogeneity outperforming homogeneous swarms, in principle [76] and on the exploration axis in dynamic conditions [77, 78], for example — but the case across the remaining axes, and across their interactions, is still to be made. Because swarm capability is emergent, the conditions under which an engineered distribution outperforms both homogeneous swarms and incidental variation [6] must be established across the behavioural hypervolume, and against the real-world mission ecology, rather than axis by axis: the work the field can now take forward.

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