

RESEARCH ARTICLE



Bio-Swarm Modular Architecture for Climbing Robots: Analytical Characterization of Critical-Mass Thresholds and Coordination Constraints

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Abstract: Climbing robotic swarms may fail because of insufficient coordination among agents or because adhesion mechanisms lose contact with the operating surface. Existing frameworks generally address these failure modes separately. This study proposes the Bio-Swarm Modular Architecture, a five-layer conceptual framework that integrates both constraints through the critical-mass threshold $N^* = \max(N_{adh}, N_{coord})$. The adhesion-derived bound is obtained from a Bernoulli reliability model, while the coordination-derived bound is formulated as a function of a baseline coordination threshold and a normalized Task Difficulty Index. The model is examined through sensitivity analysis, alternative coordination functions, correlated adhesion-failure scenarios, and a numerical case study. Under the assumptions and parameter ranges evaluated, coordination is the dominant constraint in most nominal operating conditions, whereas adhesion becomes restrictive under low-reliability or common-cause failure scenarios. A multi-criteria decision analysis (MCDA) comparison and a layer-interface specification are also presented to support architectural analysis. The proposed framework should be interpreted as a theoretical and simulation-supported tool for mission-level planning rather than as an experimentally validated robotic architecture.

Keywords: swarm robotics, climbing robots, modular robotics, adhesion reliability, coordination thresholds

1. Introduction

Ground-based swarm systems rarely encounter one of the central challenges faced by robots operating on vertical surfaces: the possibility that adhesion may fail unexpectedly at the level of an individual agent. When multiple climbing robots operate as a swarm, adhesion loss is compounded by a second failure mode, namely, the degradation or collapse of collective coordination. These mechanisms may interact, yet they are commonly addressed as separate design problems. Consequently, two fundamental questions remain insufficiently resolved: when does a climbing swarm become too small to maintain coordinated operation, and under what conditions does adhesion reliability become the dominant constraint? This study addresses both questions within a unified analytical framework.

Recent research has moved swarm robotics from abstract models of collective behavior toward applied robotic deployment, where scalability, field validation, and transfer from simulation to real environments remain central challenges [1, 2]. Studies on multi-robot task allocation further indicate that coordination

performance depends on the optimization strategy, communication efficiency, temporal constraints, and energy-aware decision-making [3, 4]. In parallel, wall-climbing robot research has advanced through adaptive adhesion mechanisms, magnetic attachment, bioinspired contact systems, and inspection-oriented designs [5, 6]. Despite these developments, the two research streams continue to evolve largely independently: swarm robotics primarily emphasizes coordination, whereas climbing robotics concentrates on adhesion and locomotion. The Bio-Swarm Modular Architecture (BSMA) addresses this separation by representing adhesion reliability and coordination emergence as competing lower-bound constraints within a single critical-mass formulation.

To identify a quantitative threshold that accounts for both limitations, we examined recent studies on applied swarm robotics, multi-robot task allocation, communication-constrained coordination, and wall-climbing robots [1, 3, 5, 7]. This review did not identify a closed-form formulation that explicitly integrates minimum viable swarm size, task difficulty, and adhesion reliability within the same analytical expression. Existing approaches have strengthened either swarm coordination or climbing adhesion, but these dimensions have not been combined sufficiently to support a mission-level decision such as determining how many

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agents are required under a specified surface condition and level of task difficulty.

This study addresses that gap by proposing the critical-mass decomposition $N^* = \max(N_{\text{adh}}, N_{\text{coord}})$, with a separate analytical derivation for the adhesion-based and coordination-based lower bounds. The framework also identifies the conditions under which each constraint becomes dominant. Under the assumptions and parameter ranges examined in this study, the coordination-derived bound is generally more restrictive than the adhesion-derived bound. This result should be interpreted as conditional on the selected coordination baseline, the mathematical representation of task difficulty, and the assumed structure of adhesion failures, rather than as a universal conclusion for all climbing robotic systems.

The contribution of this study is primarily theoretical and architectural. BSMA is not presented as an experimentally validated robotic system or as a performance-certified control architecture. Instead, it provides a structured analytical basis for examining how adhesion reliability, coordination requirements, and task difficulty jointly influence the minimum viable swarm size. The study includes a sensitivity analysis, a five-layer architectural framework, a notation system, and a comparative assessment of seven existing approaches. These elements establish a foundation for subsequent simulation, experimental calibration, and physical implementation, but they do not replace such validation.

Section 2 reviews the relevant literature and defines the theoretical gap in greater detail. Section 3 presents the BSMA architecture and derives the critical-mass threshold N^* . Section 4 reports the sensitivity analysis and comparative assessment. Section 5 discusses the assumptions, limitations, practical implications, and empirical validation requirements of the proposed framework.

2. Literature Review

2.1. Swarm robotics and group size

Recent swarm robotics literature indicates that the central challenge has shifted from demonstrating collective behavior under controlled conditions to maintaining reliable decentralized coordination under operational constraints [1, 2]. In multi-robot task allocation, coordination performance depends not only on the number of agents but also on the optimization strategy, communication efficiency, temporal constraints, energy availability, role-allocation stability, and system-level robustness [3, 4, 8]. These findings support the inclusion of a coordination-derived lower bound in BSMA. A climbing swarm must contain enough agents not only to complete the assigned task but also to sustain collective behavior when adhesion uncertainty, communication limitations, energy constraints, and dynamic role reassignment interact.

The minimum viable group size remains unresolved for physically constrained robotic swarms. Existing studies show that coordination overhead is influenced by task structure, communication uncertainty, energy constraints, environmental conditions, and the stability of role allocation [3, 4, 7, 8]. However, the reviewed literature does not establish a universally validated minimum coordination threshold for climbing robotic swarms. Accordingly, BSMA adopts $N_0 = 10$ as a nominal analytical baseline rather than as an empirical constant. This value represents a provisional reference for examining the behavior of the proposed model and must be recalibrated through climbing-specific simulations, numerical experiments, or field studies.

The selection of $N_0 = 10$ should therefore be interpreted as a modeling assumption rather than as evidence that collective coordination necessarily emerges at ten agents. Its suitability depends on the mission structure, communication topology, environmental uncertainty, robot morphology, and coordination protocol. For this reason, the effect of alternative baseline values must be examined through sensitivity analysis. Such an analysis is necessary to determine whether the predicted dominance of coordination over adhesion remains stable when the assumed emergence threshold changes.

2.2. Modular and climbing robots

Recent robotics research increasingly treats modularity and adaptive morphology as operational requirements for robots that must navigate uncertain or physically constrained environments, rather than as isolated mechanical characteristics [5, 6]. In climbing systems, this relationship becomes particularly important because morphology, contact stability, locomotion, sensing, and coordination cannot be separated at the mission level. BSMA addresses this coupling through the signal pathway extending from Layer 1 to Layer 3, where adhesion and sensory information inform locomotion, morphological adaptation, and swarm-level role reassignment.

Recent studies on wall-climbing robots further indicate that adhesion reliability is not a single hardware property. It is a system-level condition influenced by surface texture, contact geometry, payload, robot mass, locomotion mode, magnetic or suction force, environmental disturbance, vibration, and structural irregularities [5, 6, 9]. The Adhesion Reliability Coefficient (ARC) used in BSMA aggregates these heterogeneous influences into a per-cycle reliability parameter. This abstraction allows the coordination model to remain independent of the specific adhesion technology, including suction, magnetic attachment, bioinspired contact, or hybrid mechanisms. Although this simplification reduces physical detail, it provides an analytically consistent basis for comparing different adhesion systems at the mission level.

The independence assumption underlying a basic per-agent adhesion model also requires careful qualification. In realistic climbing environments, grip failures may be correlated because multiple robots can encounter the same contaminated, slippery, uneven, or structurally degraded surface region. Shared vibration, collective motion, payload imbalance, or environmental disturbances may also affect several agents simultaneously. Consequently, an independent-failure formulation should be interpreted as a baseline case rather than as a complete representation of climbing reliability. A more robust framework must distinguish between independent agent-level failures and correlated or common-cause failures that cannot be mitigated solely by increasing the number of robots.

The current framework focuses primarily on vertical surfaces because they impose a demanding gravitational condition in which the tangential component of the robot's weight is maximized. However, climbing performance also depends on surface inclination and local gravitational acceleration. On inclined surfaces, the tangential and normal components of gravitational force change with the slope angle, which may alter adhesion requirements and locomotion stability. The same consideration applies to reduced-gravity environments, including space applications, where lower gravitational loading may reduce some adhesion demands while introducing other constraints related to dust, vacuum, thermal variation, electrostatic effects, anchoring,

and communication delay. The BSMA structure may remain conceptually applicable in these environments, but ARC, the coordination baseline, and the task-difficulty parameters would require environment-specific calibration.

2.3. Coordination mechanisms with biological origins

In BSMA, Layer 3 is responsible for swarm coordination, dynamic role assignment, information dissemination, and critical-threshold monitoring. Gossip-based diffusion is adopted as a coordination abstraction because recent multi-robot studies emphasize the importance of communication-aware task allocation, coverage planning, mission replanning, and collective spatial organization [7, 10, 11]. Gossip mechanisms allow local information to propagate through the swarm without requiring a permanently centralized controller, which is consistent with the decentralized principles commonly associated with biological collective systems.

This mechanism is particularly relevant for climbing swarms because vertical displacement, partial occlusion, grip loss, energy depletion, and communication interruption may occur simultaneously. Under these conditions, the swarm must detect local failures, redistribute roles, maintain connectivity, and preserve sufficient operational capacity. The effectiveness of gossip-based coordination therefore depends on communication latency, network topology, information accuracy, convergence speed, and the number of available agents. These factors reinforce the need for a coordination-derived lower bound, but they also indicate that the threshold cannot be inferred from swarm size alone.

The relationship between task difficulty and coordination demand must likewise be defined in operational terms. Task difficulty should not be treated exclusively as a qualitative judgment. It should reflect measurable mission characteristics such as path complexity, obstacle density, communication delay, sensing uncertainty, task heterogeneity, swarm congestion, and the expected frequency of role reassignment. A reproducible Task Difficulty Index (TDI) is necessary to determine how these conditions affect the minimum number of agents required to sustain coordinated behavior.

2.4. Where prior work falls short

The principal gap is not an absence of progress in swarm robotics or wall-climbing robotics. Recent studies have advanced decentralized coordination, multi-robot task allocation, mission

planning, scalability, and swarm deployment [1, 3, 7]. In parallel, wall-climbing research has improved adhesion mechanisms, adaptive locomotion, inspection capabilities, morphological design, and contact stability [12]. However, these research areas have generally examined coordination and adhesion as separate technical problems.

What remains underdeveloped is a closed-form analytical bridge that connects minimum viable swarm size, task difficulty, adhesion reliability, and coordination requirements within a unified mission-level formulation. Existing studies do not provide a directly applicable expression that enables a mission planner to determine whether adhesion or coordination constitutes the dominant constraint under specified operating conditions. BSMA addresses this gap by representing both mechanisms as competing lower bounds in the expression

$$N^* = \max(N_{\text{adh}}, N_{\text{coord}}).$$

The proposed formulation is intended as a theoretical modeling framework rather than as an experimentally validated performance model. Its contribution lies in making the assumptions and competing constraints explicit, identifying the conditions under which each bound may become dominant, and providing a structure that can be tested through numerical simulation, platform-based modeling, and physical experiments. The framework therefore serves as a hypothesis-generating and mission-planning tool whose parameters, particularly N_0 , ARC, and the TDI, must be calibrated for specific climbing environments, robot platforms, gravitational conditions, and coordination protocols.

3. BSMA Framework Architecture

3.1. Overview

BSMA organizes control, sensing, resource allocation, and communication into five interdependent layers. The architecture is not strictly hierarchical in a top-down sense. Sensory and operational information generated in Layers 1 and 2 propagates upward, whereas mission directives generated in Layers 4 and 5 propagate downward. Layer 3 operates bidirectionally because coordination decisions depend on lower-layer information while simultaneously issuing directives that affect locomotion, resource allocation, and mission planning. Table 1 presents the overall layer structure.

Table 1
Functional responsibilities of the five-layer BSMA architecture

Layer	Component	Functional Responsibilities
L5	Mission Planning and Global Replanning	Bayesian mission-state estimation; macro-level path planning over contaminated or degraded surfaces; activation of abort and recovery protocols
L4	Adaptive Energy and Resource Management	Distributed energy estimation; adaptive transmission-power control; recharging delegation; load balancing across the swarm
L3	Swarm Coordination and Role Assignment	Gossip-based state diffusion; dynamic role negotiation; N^* threshold monitoring; attractor-based behavior switching through stigmergic cues
L2	Locomotion and Modular Reconfiguration	Limb-level trajectory control; morphology adaptation; contact-force feedback; SRP-based adhesion estimation
L1	Adhesion and Sensory Integration	Real-time vacuum or magnetic grip monitoring; surface-texture classification; ARC estimation from load-cell arrays and slip-detection IMUs

The architecture is intended as a conceptual and analytical framework rather than as an experimentally validated control system. Its purpose is to define how adhesion reliability, coordination requirements, energy management, locomotion, and mission-level decisions can be integrated within a unified critical-mass model. The operational performance of each layer must therefore be assessed through simulation, platform-specific implementation, and experimental testing.

3.2. Layer responsibilities

Layer 1 estimates the ARC using information generated by inertial measurement units (IMUs), load cells, grip sensors, and surface-classification mechanisms. It transmits grip-status and surface-condition data to the upper layers. Because adhesion performance may depend on surface contamination, structural irregularities, robot loading, inclination, vibration, and local gravitational conditions, ARC is interpreted as a conditional mission-level reliability parameter rather than as a fixed property of the adhesion mechanism.

Based on Layer 1 feedback and Layer 3 directives, Layer 2 controls limb trajectories, contact forces, locomotion, and morphological reconfiguration. Its role is to maintain stable physical interaction with the surface while adapting the robot configuration to changing environmental and mission conditions.

Layer 3 maintains the distributed swarm-state representation through gossip-based information diffusion. It monitors the

critical-mass threshold N^* , coordinates dynamic role assignment, and initiates task redistribution when the number of operational agents becomes insufficient. Its performance depends not only on swarm size but also on communication delay, network connectivity, sensing uncertainty, task heterogeneity, and the frequency of role reassignment.

Layer 4 manages distributed energy availability, transmission power, charging priorities, and workload distribution. When energy resources become limited, the layer adjusts communication and task-allocation decisions to preserve connectivity and maintain sufficient operational capacity.

Layer 5 integrates system-level information through Bayesian mission-state estimation. When the estimated probability of mission failure exceeds a predefined threshold, the layer initiates replanning, partial withdrawal, recovery, or mission-abort procedures. These decision rules are architectural specifications and require empirical calibration before operational deployment.

3.3. Notation

Table 2 defines all parameters used in the following analysis.

3.3.1. Operational interpretation of the Task Difficulty Index

The TDI represents the degree to which a mission requires explicit coordination among agents. A higher TDI corresponds to a more structured task in which routes, roles, and transitions are comparatively predictable. A lower TDI represents a more

Table 2
Notation: All parameters are defined here before use

Symbol	Definition	Notes/Domain
(ARC)	Adhesion Reliability Coefficient	Per-agent probability of successful grip during one operating cycle; $(ARC \in [0,1])$
(α)	Acceptable system-failure probability	Default value: ($\alpha = 0.05$)
(TDI)	Task Difficulty Index	Normalized measure of task structure and coordination demand; $(TDI \in [0.3,1.0])$; higher values indicate simpler or more structured tasks
(N_0)	Base coordination threshold	Nominal analytical baseline; ($N_0 = 10$)
(N^*)	Critical-mass threshold	Minimum swarm size required for mission viability
(N_{adh})	Adhesion-derived lower bound	Obtained from the independent Bernoulli model
($N_{\mathrm{adh,corr}}$)	Correlated adhesion-derived lower bound	Obtained from the common-cause failure extension
(N_{coord})	Coordination-derived lower bound	Determined from the TDI-based scaling model
(ARC_{crit})	Regime crossover value	ARC value below which adhesion becomes the binding constraint
(P_c)	Common-cause adhesion-failure probability	Probability of a shared event affecting several agents simultaneously
(γ)	Coordination-scaling exponent	Positive parameter controlling the sensitivity of (N_{coord}) to TDI
(θ)	Surface-inclination angle	($\theta \in [0^\circ, 90^\circ]$)
(g)	Gravitational acceleration	Environment-specific
(m)	Robot mass	Includes platform mass and mission payload when applicable
(p)	Payload	Mission-dependent
(s)	Surface-condition vector	Texture, contamination, roughness, moisture, and structural condition

demanding coordination environment characterized by greater uncertainty, communication dependence, role heterogeneity, or replanning requirements.

To improve reproducibility, TDI may be expressed as a normalized composite index:

$$\text{TDI} = 1 - \sum_{k=1}^K w_k x_k \quad (1)$$

subject to:

$$\sum_{k=1}^K w_k = 1, 0 \leq x_k \leq 1. \quad (2)$$

In Equation (1), x_k represents a normalized mission-complexity component and w_k represents its relative weight. Relevant components may include path complexity, obstacle density, communication delay, sensing uncertainty, task heterogeneity, swarm congestion, and expected role-reassignment frequency. The precise weights and normalization procedures must be calibrated for the target robotic platform and mission environment. Therefore, TDI is treated in the present study as an analytical mission-level parameter rather than as an experimentally validated universal index.

3.4. Deriving N^*

3.4.1. The adhesion bound

As a baseline formulation, each agent's grip state is modeled as an independent Bernoulli trial with per-cycle success probability ARC. Under the independence assumption, the probability that all Nagents fail simultaneously is:

$$P_{\text{all-fail}} = (1 - \text{ARC})^N. \quad (3)$$

Requiring this probability to remain below the acceptable system-failure probability α gives:

$$(1 - \text{ARC})^N \leq \alpha. \quad (4)$$

Solving for N produces the adhesion-derived lower bound:

$$N_{\text{adh}}(A, \text{RC}\alpha) = \left\lceil \frac{\ln(\alpha)}{\ln(1 - \text{ARC})} \right\rceil. \quad (5)$$

For $\alpha = 0.05$ and $\text{ARC} = 0.85$, Equation (5) gives $N_{\text{adh}} = 2$. The aggregation of adhesion uncertainty within ARC is consistent with recent climbing-robot literature, in which failure risk is associated with several interacting variables rather than with the adhesion mechanism alone [13, 14, 15].

The relatively low value obtained under this high-reliability scenario suggests that adhesion may not constitute the dominant lower bound under nominal conditions. However, this conclusion depends directly on the independence assumption. Real grip failures may be correlated when several robots encounter the same contaminated, uneven, slippery, or structurally degraded surface region. Shared vibration, environmental disturbance, collective motion, or common power and pressure systems may also affect multiple agents simultaneously. Consequently, Equation (5) should be interpreted as a baseline reliability model rather than as a complete representation of climbing-system failure.

3.4.2. The correlated adhesion bound

To represent shared environmental or structural disturbances, the independent model can be extended by introducing a common-cause failure probability P_c . Under this formulation, the system-failure probability is:

$$P_{\text{system-fail}} = P_c + (1 - P_c)(1 - \text{ARC})^N. \quad (6)$$

The corresponding reliability condition becomes:

$$P_c + (1 - P_c)(1 - \text{ARC})^N \leq \alpha. \quad (7)$$

When $P_c < \alpha$, the correlated adhesion-derived bound is:

$$N_{\text{adh,corr}} = \left\lceil \frac{\ln\left(\frac{\alpha - P_c}{1 - P_c}\right)}{\ln(1 - \text{ARC})} \right\rceil. \quad (8)$$

Equation (8) demonstrates that common-cause risk cannot always be mitigated by increasing the number of robots. When $P_c \geq \alpha$, the shared failure event alone exceeds the acceptable system-risk threshold. Under such conditions, additional agents do not restore compliance with the required reliability level. The appropriate response would involve surface reassessment, environmental mitigation, mission replanning, or redesign of the adhesion system.

This extension does not provide a complete stochastic dependence model, but it offers a more realistic comparison with the independent Bernoulli assumption and clarifies the conditions under which adhesion redundancy becomes insufficient.

3.4.3. The coordination bound

Recent swarm robotics and multi-robot task-allocation studies indicate that coordination overhead increases with task complexity, communication limitations, dynamic role assignment, and energy constraints [16, 17, 8]. Because climbing swarms operate under additional physical and environmental restrictions, BSMA adopts $N_0 = 10$ as a nominal analytical baseline rather than as an empirically established constant.

The baseline coordination bound is defined as:

$$N_{\text{coord}}(\text{TDI}) = \left\lceil \frac{N_0}{\text{TDI}} \right\rceil. \quad (9)$$

At $\text{TDI} = 0.50$, Equation (9) gives $N_{\text{coord}} = 20$. At $\text{TDI} = 0.90$, it gives $N_{\text{coord}} = 12$. These values illustrate the intended direction of the model: less structured tasks require a larger coordination reserve, whereas more structured tasks require fewer agents to maintain collective organization.

The value $N_0 = 10$ should not be interpreted as a universal emergence threshold for climbing swarms. It is a provisional reference value that must be recalibrated using climbing-specific simulation or field data. The effect of alternative values of N_0 should therefore be examined through sensitivity analysis.

A generalized form of the coordination model is:

$$N_{\text{coord}}(T, \text{DI}\gamma) = \lceil N_0 \text{TDI}^{-\gamma} \rceil, \quad (10)$$

where γ controls the sensitivity of coordination requirements to task difficulty. The baseline formulation in Equation (9) corresponds to $\gamma = 1$. Values below 1 represent a sublinear response, whereas values above 1 represent a stronger increase in coordination requirements as TDI decreases.

3.4.4. Why the inverse TDI scaling is defensible

The inverse TDI relationship is an analytical approximation rather than a direct consequence of fundamental coordination dynamics. Its justification involves both the expected direction of the relationship and the mathematical properties of the selected function.

First, lower TDI values represent missions with greater uncertainty, weaker task structure, and stronger dependence on explicit inter-agent coordination. Under these conditions, robots must exchange more information concerning roles, positions, coverage, task handoffs, and replanning decisions. This interpretation is consistent with recent multi-robot task-allocation and swarm-coordination literature, which shows that loosely structured missions require stronger communication, dynamic role allocation, coverage negotiation, and replanning capacity [7, 18, 19].

Second, the inverse form is monotonic, parsimonious, and free of additional fitted parameters when $\gamma = 1$. It maps $\text{TDI} \in (0, 1)$ to a positive scaling of N_0 , thereby preserving the expected direction of the relationship. Nevertheless, the function should not be interpreted as an empirically validated law.

Alternative specifications may include a linear model:

$$N_{\text{coord,lin}} = [N_0 [1 + \beta (1 - \text{TDI})]], \quad (11)$$

or an exponential model:

$$N_{\text{coord,exp}} = [N_0 e^{\beta(1-\text{TDI})}]. \quad (12)$$

Comparing the inverse, generalized power, linear, and exponential formulations is necessary to determine whether the predicted dominance of coordination remains stable across alternative mathematical assumptions. The final functional form should be calibrated through simulation or experimental observations using platforms such as ARGoS, Webots, or equivalent robotic environments.

3.4.5. Combining the bounds

Under the independent adhesion model, the critical-mass threshold is:

$$N^* = \max(N_{\text{adh}}, N_{\text{coord}}). \quad (13)$$

Under the common-cause failure extension, the corresponding threshold becomes:

$$N_{\text{corr}}^* = \max(N_{\text{adh,corr}}, N_{\text{coord}}). \quad (14)$$

The crossover ARC value is obtained by setting the independent adhesion and coordination bounds equal. Using the continuous form before applying the ceiling operator gives:

$$\text{ARC}_{\text{crit}}(\text{TDI}) = 1 - \alpha^{\text{TDI}/N_0}. \quad (15)$$

For $\alpha = 0.05$, $N_0 = 10$, and $\text{TDI} = 0.50$, Equation (15) produces an ARC_{crit} value of approximately 0.14. Therefore, the crossover value is not a fixed characteristic of climbing swarms. It changes according to the acceptable failure probability, the coordination baseline, task difficulty, the functional form selected for N_{coord} , and the assumed dependence among adhesion failures.

3.4.6. Gravity and surface-inclination considerations

The baseline BSMA formulation focuses on vertical surfaces because they represent a demanding climbing condition in which the tangential gravitational load reaches its maximum value relative to robot weight. The tangential and normal gravitational components can be represented as:

$$F_t = mg \sin(\theta), \quad (16)$$

$$F_n = mg \cos(\theta) \quad (17)$$

For a vertical surface, $\theta = 90^\circ$, and the tangential component becomes $F_t = mg$. For inclined surfaces, the tangential load decreases as the inclination angle is reduced. These changes affect contact stability, locomotion requirements, and the reliability of the adhesion mechanism.

Within BSMA, these effects can be incorporated through an effective adhesion coefficient:

$$\text{ARC}_{\text{eff}} = \text{ARC}(\theta, g, m, p, s). \quad (18)$$

Equation (18) indicates that adhesion reliability may depend on surface inclination, gravitational acceleration, robot mass, payload, and surface conditions. The current study does not independently calibrate these variables, so the formulation should be interpreted as an extension of the framework rather than as a validated physical model.

In reduced-gravity environments, the gravitational load decreases, but other constraints may become more important, including dust, vacuum conditions, thermal variation, electrostatic effects, anchoring uncertainty, and communication delay. The BSMA structure remains conceptually applicable to such environments, but ARC, TDI, N_0 , and the failure-dependence assumptions must be recalibrated for the target operational setting.

Within the high-reliability range shown in Table 3, the coordination-derived bound is larger than the adhesion-derived bound for every parameter combination. This result indicates that coordination is the binding constraint under the nominal independent-failure assumptions represented in the table. It does not demonstrate that coordination necessarily dominates under low-ARC conditions, correlated adhesion failures, alternative values of N_0 , or different functional definitions of N_{coord} .

Consequently, the table should be interpreted as a restricted high-reliability sensitivity analysis rather than as evidence of a universal operating regime. A complete robustness assessment requires extending the ARC range, examining alternative coordination baselines and scaling functions, and evaluating common-cause adhesion scenarios. Under the current nominal assumptions, improvements in adhesion reliability above the crossover region do not reduce the predicted value of N^* , although they may still improve safety, fault tolerance, and mission continuity.

4. Analytical Results

4.1. Coordination dominates

Table 3 shows that every combination of ARC between 0.75 and 0.95 and TDI between 0.30 and 0.90 is coordination-bound. Across this restricted high-reliability range, N_{coord} exceeds N_{adh} for all evaluated parameter combinations. For example, at $\text{TDI} = 0.30$, the coordination model requires 34 agents, whereas

Table 3

Sensitivity analysis of N^* under the independent adhesion model. All values are computed from Equations (5), (9), and (13), with $\alpha = 0.05$ and $N_0 = 10$. N_c denotes N_{coord} for the corresponding TDI value

TDI/ARC	ARC = 0.75	ARC = 0.80	ARC = 0.85	ARC = 0.90	ARC = 0.95
TDI = 0.30 ($N_c = 34$)	34	34	34	34	34
TDI = 0.40 ($N_c = 25$)	25	25	25	25	25
TDI = 0.50 ($N_c = 20$)	20	20	20	20	20
TDI = 0.60 ($N_c = 17$)	17	17	17	17	17
TDI = 0.70 ($N_c = 15$)	15	15	15	15	15
TDI = 0.80 ($N_c = 13$)	13	13	13	13	13
TDI = 0.90 ($N_c = 12$)	12	12	12	12	12

the adhesion-derived lower bound remains substantially smaller throughout the ARC range examined.

This result indicates that, under the nominal independent-failure assumptions, improvements in adhesion reliability do not reduce the predicted critical swarm size once ARC exceeds the crossover boundary. Instead, reductions in N^* would depend primarily on changes that decrease the coordination requirement, such as restructuring the mission to increase the effective TDI, improving the coordination protocol, reducing communication latency, stabilizing role allocation, or accelerating gossip convergence.

This interpretation is consistent with deployment-oriented swarm robotics research, in which coordination reliability, task allocation, communication efficiency, and system-level scalability remain central constraints even when the individual robotic platforms are technically capable [2, 20, 21]. It also provides a more precise interpretation of recent adhesion-centered developments in wall-climbing robotics. Improved adhesion remains essential for safety, operational continuity, and fault tolerance, but it does not necessarily reduce the minimum viable swarm size when the coordination-derived bound remains dominant [22].

The result must nevertheless be interpreted as conditional on the assumptions of the model. In particular, it depends on the selected value of N_0 , the inverse relationship between TDI and N_{coord} , the independent Bernoulli representation of adhesion failures, and the parameter ranges examined. It should not be generalized to low-reliability surfaces, correlated grip failures, alternative coordination functions, or climbing platforms with substantially different emergence thresholds.

The effect of N_0 illustrates this dependence. If the climbing-specific coordination baseline were lower than the nominal value derived from the general swarm literature, the coordination bound would decrease, and the crossover between adhesion and coordination would shift. For example, reducing N_0 from 10 to 5 would alter the value of ARC_{crit} and reduce the predicted swarm size across the TDI range. This sensitivity confirms that N_0 must be calibrated through climbing-specific simulation or experimental observations before the model can support operational deployment decisions.

4.2. Regime boundaries

The analytical formulation identifies two principal operating regimes. In the coordination-bound regime,

$$\text{ARC} > \text{ARC}_{\text{crit}}(\text{TDI}),$$

and the critical swarm size is determined by:

$$N^* = N_{\text{coord}}.$$

Within this regime, variations in adhesion reliability do not change the predicted value of N^* , provided that ARC remains above the crossover threshold. The primary design priorities are therefore coordination-protocol performance, communication reliability, task decomposition, role-allocation stability, and convergence speed. Adhesion monitoring remains necessary for safety, but improvements in adhesion alone do not reduce the critical swarm size predicted by the model.

In the adhesion-bound regime,

$$\text{ARC} < \text{ARC}_{\text{crit}}(\text{TDI}),$$

and the critical swarm size is determined by:

$$N^* = N_{\text{adh}}.$$

Under these conditions, the minimum viable swarm size becomes increasingly sensitive to grip reliability. Surface degradation, contamination, structural irregularities, vibration, or other shared environmental disturbances may increase the number of agents required to maintain the acceptable system-failure probability. Appropriate responses include proactive replacement of degraded agents, intensified adhesion telemetry, surface reassessment, route modification, and mission-level replanning.

The boundary $\text{ARC}_{\text{crit}}(\text{TDI})$ can therefore be interpreted as an operational decision variable. Layer 1 continuously estimates ARC from grip and surface data, while Layer 5 evaluates the position of the swarm relative to the crossover boundary. When the system approaches or crosses the boundary, the architecture may modify task allocation, communication resources, agent deployment, or recovery procedures.

This decision mechanism can be implemented incrementally. It does not require the complete BSMA architecture to be physically realized before the crossover logic is evaluated. A mission-planning module could estimate ARC and TDI from available telemetry and task information, calculate N_{adh} , N_{coord} , and N^* , and determine which system constraint requires intervention.

The two-regime interpretation is subject to an important limitation. Under correlated or common-cause adhesion failures, the independent crossover boundary may underestimate system risk. If the common-cause failure probability approaches or exceeds α , increasing the number of agents may no longer restore the required reliability level. In that situation, the system cannot be characterized solely by the competition between N_{adh} and N_{coord} ;

environmental mitigation or adhesion-system redesign becomes necessary.

4.3. Comparative evaluation

A multi-criteria decision analysis (MCDA) was used to compare eight approaches across five architecture-level criteria. The criteria were vertical adhesion integration, with a weight of 0.30; swarm-coordination capability, with a weight of 0.25; modular reconfiguration, with a weight of 0.20; energy management, with a weight of 0.15; and mission replanning, with a weight of 0.10. These criteria reflect the principal operational requirements identified for climbing swarm missions. Recent swarm and climbing-robot literature increasingly emphasizes adhesion robustness, distributed coordination, adaptive or modular locomotion, energy-aware allocation, and mission-level replanning [1, 3, 23].

Each approach was scored from 1 to 4. A score of 1 indicates that the capability is absent or only minimally represented, whereas a score of 4 indicates that it is explicitly formalized and integrated into the reported architecture. The weighted total was calculated as:

$$S_i = \sum_{j=1}^m w_j s_{ij}, \quad (19)$$

where S_i is the weighted total for approach i , w_j is the weight assigned to criterion j , and s_{ij} is the score assigned to approach i for criterion j .

As shown in Table 4, under the selected weights and author-assigned scores, BSMA obtains a weighted total of 3.85. Modular self-reconfigurable robotics (SR) [24] receives the second-highest total, 2.50, because it provides strong modular reconfiguration but more limited integration of vertical adhesion and swarm-level coordination. Approaches derived from pure swarm coordination, including Reynolds Boids [25], perform strongly in decentralized collective behavior but do not explicitly integrate adhesion or modular reconfiguration.

These results describe the extent to which the reported architecture of each approach addresses the selected design criteria. They do not constitute an experimental comparison of physical performance, reliability, computational efficiency, or mission success. In particular, the BSMA score reflects the capabilities

proposed by the framework rather than independently measured outcomes.

The MCDA comparison is exploratory and contains several sources of subjectivity. The criteria, weights, and scores were assigned by the authors, and no independent panel, inter-rater reliability procedure, or uncertainty analysis was conducted. In addition, the comparison may favor BSMA because the proposed architecture was designed to address all five selected criteria explicitly. The resulting ranking should therefore be interpreted as an architecture-coverage assessment rather than as evidence that BSMA outperforms the other approaches.

The comparison should be strengthened in future work through independent expert scoring, inter-rater agreement analysis, alternative weighting scenarios, and sensitivity analysis. Varying the criterion weights would help determine whether the ranking remains stable or depends strongly on the initial author-assigned configuration.

4.4. Layer-interface specification

Table 5 translates the conceptual architecture into a preliminary set of layer-level information exchanges and decision conditions. The update rates are design targets rather than experimentally validated requirements. Similarly, the decision rules are simplified threshold conditions intended to illustrate how the analytical model could inform a future implementation.

The Layer 1 to Layer 2 decision rule has been reformulated because an ARC value below ARC_{crit} does not necessarily imply that increasing N is sufficient. Under independent failures, additional agents may restore the required reliability level. Under correlated or common-cause failures, however, the appropriate intervention may involve route modification, environmental reassessment, or redesign of the adhesion mechanism.

The Layer 4 to Layer 5 interface may require substantially more complex decision logic in highly dynamic environments. Multi-hypothesis state estimation, probabilistic filtering, predictive energy modeling, and uncertainty-aware mission planning may be necessary when surface conditions, communication quality, and agent availability change simultaneously. The single-threshold rules presented in Table 5 should therefore be interpreted as preliminary control abstractions rather than as validated operational policies.

Table 4
MCDA comparative scoring matrix and weighted totals

Approach	Vert. Adhesion (0.30)	Swarm Coord. (0.25)	Mod. Reconfig. (0.20)	Energy Mgmt. (0.15)	Replanning (0.10)	Weighted Total	Refs.
Weight	0.30	0.25	0.20	0.15	0.10	1.00	Scale 1-4
BSMA (proposed)	4	4	4	3	4	3.85	[This work]
Reynolds Boids	1	4	1	2	2	2.00	[3]
Modular SR	2	2	4	2	3	2.50	[12]
Swarm-only	1	4	1	2	3	2.10	[7]
Bio-loco	3	2	2	3	2	2.45	[18]
Stigmergic	2	3	1	2	3	2.15	[21]
Task allocation	1	3	2	2	4	2.15	[23]
Collective manipulation	2	3	3	2	2	2.45	[26]

Table 5
Layer-interface specifications, preliminary update-rate targets, and conceptual decision rules requiring simulation-based and experimental calibration

Interface	Primary Inputs	Primary Outputs	Update Rate	Failure Mode	Decision Rule
L1 → L2	Surface-texture map; load-cell readings	ARC estimate; grip count per agent	10 Hz	Grip-loss event; IMU-detected slip	$ARC < ARC_{crit} \rightarrow$ reassess swarm size, surface condition, or route
L2 → L3	Limb-force feedback; morphology state	Formation error; gap-coverage map	5 Hz	Role conflict; unstable formation	$N < N^* \rightarrow$ activate recruitment or task reallocation
L3 → L4	Agent roles; swarm-state vector; task graph	Task-reassignment directive; charging schedule	1 Hz	Coordination deadlock; connectivity degradation	TDI boundary crossing $\rightarrow$ trigger Layer 5 replanning
L4 → L5	Energy map; agent-health states	Replanning request; partial-abort signal	0.5 Hz	Conflicting directives; insufficient energy reserve	$P_{fail} > 0.15 \rightarrow$ evaluate recovery or mission abort

5. Discussion

5.1. What this paper does and does not claim

BSMA is a theoretical and architectural framework rather than a performance-validation study. This positioning is consistent with the current state of the field. Recent literature has advanced swarm coordination, multi-robot task allocation, wall-climbing adhesion, and inspection robotics, but it remains unclear how these components should be translated into explicit mission-level deployment thresholds [27, 28, 29]. BSMA contributes at this analytical level by defining two lower-bound constraints on the minimum viable swarm size, identifying the operating regime in which each constraint becomes dominant, and organizing the relevant system functions within a five-layer architecture.

The study does not present a physical prototype, platform-level implementation, robotic simulation, or empirical measurement of the proposed parameters [30]. Accordingly, the framework should not be interpreted as evidence of experimentally demonstrated performance, reliability, or mission success. Its contribution lies in formalizing the relationship among adhesion reliability, coordination requirements, task difficulty, and minimum swarm size in a manner that can subsequently be tested and recalibrated.

The decomposition

$$N^* = \max(N_{adh}, N_{coord})$$

is not a predictive model in the statistical sense. It is an analytical decision rule that identifies which constraint determines the minimum deployment size once the required parameter values have been estimated. If ARC is obtained from repeated adhesion tests or operational telemetry, and TDI is derived from measurable mission characteristics, N^* can provide a theoretically grounded lower-bound estimate. If these parameters are assigned without empirical support, the resulting threshold remains provisional. The validity of the estimate therefore depends directly on the quality, representativeness, and calibration of the inputs [31].

5.2. The most vulnerable piece

The coordination-derived bound is the less firmly established component of the framework. The adhesion-derived bound

follows directly from the specified Bernoulli reliability model, although its realism depends on the independence assumption. By contrast, N_{coord} depends on two stronger assumptions: first, that a baseline derived from general swarm-emergence studies can be provisionally transferred to climbing tasks; and second, that the relationship between task difficulty and coordination requirements can be approximated through an inverse or generalized power function [32].

The nominal value $N_0 = 10$ is therefore not treated as a universal coordination threshold. Climbing swarms operate under constraints that differ substantially from those affecting ground-based systems, including adhesion uncertainty, vertical load, restricted contact geometry, partial occlusion, and surface-dependent locomotion. These conditions may increase or reduce the number of agents required to sustain collective behavior. A climbing-specific value of N_0 must consequently be obtained through simulation or experimental calibration.

The functional relationship between TDI and N_{coord} is also uncertain. If N_0 for climbing tasks is closer to 5 than to 10, the coordination-derived lower bound decreases, and the crossover value ARC_{crit} shifts accordingly. Similarly, if the response to task difficulty is sublinear rather than hyperbolic, high-TDI missions would require fewer agents than predicted by the baseline formulation. Conversely, a superlinear relationship would increase the estimated coordination requirement for difficult missions.

These uncertainties do not invalidate the analytical structure, but they limit the generalizability of its numerical outputs. The model should therefore be interpreted as a falsifiable hypothesis concerning the relationship among coordination demand, adhesion reliability, and minimum swarm size. Its principal methodological value lies in making the underlying assumptions explicit and identifying the empirical evidence required to revise them.

5.3. Limitations

The study has several limitations that affect the interpretation and practical applicability of its findings. First, the independent Bernoulli formulation of N_{adh} may underestimate risk when grip failures are spatially or temporally correlated. Such dependence may arise when multiple robots encounter the same contaminated surface region, structural defect, vibration source, environmental

disturbance, or shared mechanical or energy failure [33]. Although the common-cause extension provides a more cautious formulation, it remains a simplified representation of failure dependence.

Second, the baseline N_0 is informed by literature on general or ground-based swarm systems rather than by experiments involving climbing robotic swarms. Its transferability to vertical, inclined, or reduced-gravity environments has not been established. The influence of gravity, slope, payload, surface condition, and robot morphology is incorporated conceptually through ARC and related parameters, but these relationships have not been independently calibrated.

Third, the TDI remains a model-dependent construct. Although the framework identifies measurable components such as path complexity, obstacle density, communication delay, sensing uncertainty, task heterogeneity, swarm congestion, and role-reassignment frequency, the weighting and normalization procedures require empirical validation. Different parameterizations may produce different estimates of N_{coord} .

Fourth, the MCDA comparison is based partly on author-assigned criteria, weights, and scores. It has not undergone independent expert assessment, inter-rater reliability testing, or uncertainty analysis. The comparison therefore evaluates architectural coverage rather than experimentally demonstrated superiority. BSMA may receive a higher score because it was explicitly designed to include all selected criteria.

Fifth, the framework has not been evaluated through robotic simulation, prototype implementation, or field experimentation. The update rates and threshold rules reported in the layer-interface specification are design targets rather than validated control parameters. Moreover, the technical implementation of gossip diffusion, attractor-based behavior switching, Bayesian mission-state estimation, communication recovery, and fault-tolerant role reassignment remains unspecified [34].

Finally, the analytical results depend on the selected parameter ranges and mathematical assumptions. The conclusion that coordination dominates adhesion applies only to the nominal high-reliability scenarios examined under the current formulation. It should not be generalized to low-ARC environments, correlated failures, substantially different values of N_0 , or alternative coordination-scaling functions.

These limitations identify the conditions under which the framework can be tested, refined, or rejected. They therefore define the principal empirical and methodological priorities for subsequent research.

5.4. What would make this stronger

The most important next step is a simulation study specifically designed to estimate coordination-emergence thresholds for climbing swarms. A platform such as ARGoS, Webots, Gazebo, or an equivalent multi-robot environment could be used to evaluate 5–25 agents across several TDI levels on vertical and inclined surfaces. The study should vary communication latency, role heterogeneity, adhesion loss, agent attrition, energy availability, and surface disturbance to determine how these factors affect N_{coord} , mission success, and recovery capacity.

Such a study would permit direct comparison among the inverse, generalized power, linear, and exponential coordination functions. It would also support empirical estimation of N_0 and γ , rather than relying on nominal values. Repeated simulation under alternative coordination protocols would further determine

whether the predicted threshold is architecture-specific or relatively stable across different decentralized mechanisms.

The adhesion component should be strengthened through repeated reliability testing under controlled surface and loading conditions. ARC distributions could be estimated across combinations of surface texture, contamination, inclination, payload, robot mass, vibration, and adhesion technology. These measurements would allow the independent Bernoulli model to be compared with correlated, spatially clustered, or common-cause failure models.

The MCDA evaluation would benefit from independent expert scoring, explicit evidence coding, inter-rater agreement analysis, and sensitivity testing across alternative weight configurations. This procedure would clarify whether the comparative ranking is robust or primarily determined by the authors' initial criteria and assumptions.

A subsequent experimental phase should implement selected BSMA layers on a physical or high-fidelity simulated platform. At minimum, this implementation should evaluate ARC estimation, threshold monitoring, communication-driven role reassignment, energy-aware task redistribution, and mission-level replanning. These steps would transform BSMA from a conceptual analytical framework into a progressively calibrated and empirically testable architecture.

6. Conclusions

This study developed a critical-mass threshold for climbing robotic swarms by integrating two analytically distinct components within the expression $N^* = \max(N_{\text{adh}}, N_{\text{coord}})$. The adhesion-derived bound was formulated through a Bernoulli reliability model, while the coordination-derived bound was established from a nominal swarm-emergence baseline and an explicit inverse relationship with the TDI. These elements were incorporated into a five-layer BSMA architecture that connects adhesion monitoring, locomotion and reconfiguration, swarm coordination, energy management, and mission-level replanning.

Under the nominal parameter ranges and modeling assumptions examined, the coordination-derived bound was more restrictive than the adhesion-derived bound. This result indicates that, in high-reliability scenarios, the predicted minimum viable swarm size depends primarily on task structure, communication performance, role-allocation stability, and coordination efficiency. However, this conclusion is conditional on the selected value of N_0 , the assumed functional relationship between TDI and N_{coord} , and the independence of adhesion failures. It should therefore not be generalized to low-reliability surfaces, correlated or common-cause grip failures, alternative coordination models, or climbing systems with different emergence thresholds.

The analysis also clarifies that improvements in adhesion remain essential for safety, operational continuity, and fault tolerance, even when they do not reduce N^* within the nominal coordination-bound regime. When ARC approaches or falls below the crossover boundary, or when common-cause failures become relevant, adhesion may become the dominant constraint and may require surface reassessment, environmental mitigation, route modification, or redesign of the attachment mechanism.

The principal contribution of BSMA is therefore not an experimentally validated performance claim, but a structured analytical framework for identifying which system constraint governs the minimum deployment size under specified mission conditions. The layer-interface specification and MCDA comparison provide

an initial basis for implementation planning, although both remain conceptual and require independent validation.

Future research should prioritize the algorithmic specification of gossip diffusion, attractor-based behavior switching, and Bayesian mission-state estimation; empirical measurement of ARC distributions under different surfaces, payloads, inclinations, and gravitational conditions; and simulation-based calibration of N_0 , TDI, and N_{coord} for climbing-specific missions. These steps are necessary to determine whether the proposed thresholds remain valid across different platforms and environments and to advance BSMA from an analytical framework toward a calibrated and experimentally testable robotic architecture.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Edwin Gerardo Acuña Acuña: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Sacramento Cruz-Doriano:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing – review & editing, Supervision. **Maria Teresita de Jesús Chi-Chan:** Conceptualization, Validation, Investigation, Writing – review & editing, Visualization.

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How to Cite: Acuña Acuña, E. G., Cruz-Doriano, S., & Chi-Chan, M. T. de J. (2026). Bio-Swarm Modular Architecture for Climbing Robots: Analytical Characterization of Critical-Mass Thresholds and Coordination Constraints. *Journal of Climbing and Walking Robots*. <https://doi.org/10.47852/bonviewJCWR62029937>