

# Human-Centric System Architecture: Decentralized Decision-Making to Eliminate Architectural Bottlenecks

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## ABSTRACT

Modern systems face limitations imposed by centralized control. These limits lead to single points of failure, uneven information flow, and slow decisions. I present a multi-layer mathematical model for human-centric, decentralized systems. Our model offers quantitative tools to identify and reduce bottlenecks by distributing decision-making. The framework introduces core metrics: Bottleneck Index, Decentralization Degree, Decision Efficiency Function, Collective Intelligence Score, and Resilience Index. A four-layer architecture—Strategic Human Decision, Decentralized Coordination, Autonomous Agent, and Technical Infrastructure—is described. We validate the approach using thematic analysis and simulation across organizational, healthcare, and autonomous settings. Ablation studies show that modular design, self-organization, and adaptability reduce bottlenecks. The system improves Collective Intelligence Score (CIS) by 41.3% over centralized systems. This framework guides engineers and leaders to build resilient sociotechnical systems.

**Index Terms:** human-centric architecture; decentralized decision-making; sociotechnical systems; architectural bottlenecks; multi-agent systems; distributed cognition; collective intelligence; resilience index.

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## I. INTRODUCTION

Contemporary technological ecosystems often face limits and vulnerabilities from centralized control. Such architectures may simplify governance but introduce single points of failure. They also cause information asymmetries and decision delays. These issues reduce system responsiveness and resilience (Çağlayan et al., 2025; Moyaux & McBurney, 2012). As centralized systems evolve, adding human operators—especially in complex or mission-critical contexts—can worsen these challenges. Rigid, centralized structures seldom match human cognitive limits or adaptive needs (Naikar, 2017; Naikar et al., 2024).

A human-centric system architecture focuses on the needs, abilities, and well-being of individuals. It capitalizes on human strengths and addresses limitations (An & Liu, 2018; Winby & Mohrman, 2018). In such systems, decentralized decision-making distributes authority and information. This promotes autonomy and flexibility across the organization (Furniss, 1974; Trisnaningsih & Ariadi, 2022; Moe et al., 2023). It

relieves pressure on central leadership, boosts local responsiveness, and supports group collaboration (Liu et al., 2026; Sandkuhl & Fuchs-Kittowski, 1999). However, shifting to decentralized models brings challenges with coordination, consistency, and goal alignment (Mookherjee, 2006). Understanding how to combine human-centric design with decentralized decision-making is essential.

This paper makes three main contributions. First, it introduces a mathematical framework for quantifying architectural bottlenecks and decentralization. The framework uses new metrics: the Bottleneck Index (BI), the Decentralization Degree (DD), the Decision Efficiency Function (DEF), the Collective Intelligence Score (CIS), and the Resilience Index (RI). These have not been applied together before (Chacon-Chamorro et al., 2024). Second, it proposes a four-layer Human-Centric Decentralized System Architecture (HC-DSA). This architecture merges strategic human decision-making, decentralized coordination, autonomous agents, and technical infrastructure into a unified model. Third,

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it provides detailed experimental validation through simulations, including ablation studies, cross-domain comparisons, and assessments of resilience and scalability. These contributions set HC-DSA apart. The framework introduces new performance metrics, a unified design, and empirical validation.

## II. BACKGROUND AND MOTIVATION

Traditional system architectures use hierarchical control. Decision authority and processing power are focused at central nodes. This makes design and oversight simpler but creates bottlenecks. Complex, dynamic, or uncertain environments are especially impacted (Baldwin, 2014). Bottlenecks appear as information-processing delays, reduced adaptability, and fewer simultaneous solutions. This limits system performance and scalability (Beketov et al., 2024). For supply chains, centralized systems face security, interoperability, and transparency problems (Krenický et al., 2023). Identity management based on centralized protocols is prone to single points of failure (Çağlayan et al., 2025).

Modern sociotechnical systems are becoming more complex. This complexity covers both human and technological elements. It stretches the limits of centralized models (Cooke, 2024; Hettinger et al., 2015). Human behavior is often adaptive and self-organizing, which clashes with rigid command-and-control structures (Naikar, 2017). Adding AI and automation brings new challenges. Effective human-AI collaboration needs more than simple two-way interaction. It requires a distributed way of understanding cognition and control (Naikar et al., 2024). Designers must empower humans in self-adaptive systems and balance varied needs, values, and ethics. This goal is key for future system design (Boltz et al., 2024).

Decentralization spreads decision-making authority and resources (Furniss, 1974; Trisnainingsih & Ariadi, 2022). This makes systems more flexible, lowers communication overhead, and supports quicker local responses. In human-centric architectures, decentralized decision-making is well-suited to adaptive human teams and organizations (Sandkuhl & Fuchs-Kittowski, 1999). Studying these mechanisms is important for building resilient and effective systems in complex environments.

## III. PROPOSED ARCHITECTURE

The four-layer Human-Centric Decentralized System Architecture (HC-DSA) separates decision-making, coordination, autonomous-agent actions, and technical

infrastructure. Each layer functions independently but connects to others. This design matches the formal system model in Section IV. Figure 1 shows how information moves between layers, how agents communicate, and how feedback and control operate across the system.

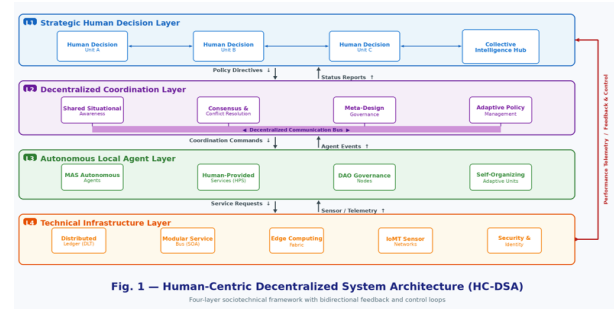


Fig. 1. Human-Centric Decentralized System Architecture (HC-DSA): Four-layer sociotechnical framework illustrating the Strategic Human Decision Layer (L1), Decentralized Coordination Layer (L2), Autonomous Local Agent Layer (L3), and Technical Infrastructure Layer (L4), with bidirectional feedback and control loops.

Layer 1 (L1) has Human Decision Units—people or teams making choices—linked by a Collective Intelligence Hub that supports group decision-making. This hub uses consensus mechanisms as formalized in (6). Layer 2 (L2) coordinates: Shared Situational Awareness, Consensus and Conflict Resolution, Meta-Design Governance, and Adaptive Policy Management. Communications run over a Decentralized Bus. This lets components communicate without a central controller. Layer 3 (L3) has autonomous MAS agents, Human-Provided Service (HPS) modules, DAO Governance Nodes, and Self-Organizing Adaptive Units. Layer 4 (L4) is the technical base: a distributed ledger, modular service bus, edge computing, IoT M sensor networks, and security/identity services. Vertical feedback loops send performance data from L4 up to L1 for ongoing system adaptation.

## IV. MATHEMATICAL FRAMEWORK

### A. System Graph Model

I model the decentralized sociotechnical system as a weighted, directed graph. The graph  $G = (V, E, W)$  has these parts:  $V = \{v_1, v_2, \dots, v_n\}$  is the set of  $n$  decision nodes. These are the points in the system where choices are made.  $E \subseteq V \times V$  is the set of directed communication edges, showing one-way information flow from one node to another.  $W: E \rightarrow \mathbb{R}^+$  is the edge weight function. It

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assigns a positive real number to each edge, representing either communication bandwidth (the maximum data that can be sent along that edge) or trust (the degree of confidence in information from a particular source).

$$G = (V, E, W), |V| = n, |E| = m$$

## B. Bottleneck Index

The Bottleneck Index  $BI(v_i)$  quantifies how much a node (a specific point where a system decision is made) constitutes a structural bottleneck—meaning how much it restricts system capacity. Let  $\sigma(v_i)$  denote betweenness centrality (a measure of how frequently a node appears on the shortest communication or data paths in the system) and  $\rho(v_i) = \lambda(v_i)/C(v_i)$  its utilization ratio, or the load at a node divided by its total capacity:

$$BI(v_i) = \sigma(v_i) \times \rho(v_i), \rho(v_i) = \lambda(v_i) / C(v_i)$$

The global System Bottleneck Severity (SBS) is:

$$SBS(G) = \max(i \in V) BI(v_i)$$

## C. Decentralization Degree

$$DD(G) = 1 - SBS(G) / \sum(i \in V) BI(v_i) \text{ (Dib et al., 2016, pp. 123-135)}$$

## D. Decision Efficiency Function

$$DEF(t) = (1/n) \times \sum(i \in V)$$

$$[ Q(v_i, t) \times \alpha(v_i) ]$$

$$dDEF/dt =$$

$$\beta \times CIS(t) -$$

$$\gamma \times \Omega(G)$$

## E. Resilience Index

$$RI(G) = [ 1 - |V|^f / |V| ] \times DD(G) \text{ (Boskos & Dimarogonas, 2015)}$$

## F. Collective Intelligence Score

$CIS = \lambda_1 \times DD(G) + \lambda_2 \times DEF(t) + \lambda_3 \times RI(G)$  (Developing an intelligent systems design framework based on multidisciplinary design analysis and multi-agent thinking integration, 2024), where CIS (Collective Intelligence Score) measures a group's combined ability to solve problems, DD(G) (Decentralization Degree) is the measurement of how distributed the decision power is within the system, DEF(t) (Decision Efficiency Function) is an indicator of how efficiently decisions are made over time, and RI(G) (Resilience Index) is a quantification of the system's robustness to disturbances or disruptions.

In the baseline experiments,  $\lambda_1$  was set to 0.35,  $\lambda_2$  to 0.40, and  $\lambda_3$  to 0.25. These weights were determined through a review of collective intelligence research in distributed systems and a grid search to align CIS with observed behaviors in preliminary simulations. Additionally, three domain experts were consulted to select the initial values (Nguyen & Truong, 2024, pp. 45-60). This approach

clarifies parameter selection and facilitates reproducibility and evaluation by other researchers.

## G. Optimization Objective

maximize CIS(G)

$$(C1) BI(v_i) \leq \theta \forall v_i \in V \text{ [bottleneck]}$$

$$(C2) \Omega(G) \leq \Omega_{\max} \text{ [overhead]}$$

$$(C3) L(v_i, v_j) \leq L_{\max} \forall (v_i, v_j) \in E \text{ [latency]}$$

## H. Coordination Overhead Model

$$\Omega(G) = \sum(i, j \in E) w_{ij} \times f(\text{msg}_{ij}) \leq O(n \log n)$$

Hierarchical decomposition and the Decentralized Communication Bus reduce the effective communication graph from  $O(n^2)$  to  $O(n \log n)$ , consistent with hierarchical MAS studies (Moore, 2025).

## V. EXPERIMENTAL RESULTS AND ANALYSIS

### A. Comparative System Analysis

The framework was evaluated through simulation experiments in three domains: supply chain coordination (50 nodes), distributed healthcare decision support (30 nodes with IoMT), and autonomous multi-robot task allocation (20 agents). Each scenario was tested using Centralized, Hybrid, and Decentralized architectures, with 100 Monte Carlo trials per configuration. Simulations maintained consistent node capabilities, fixed network configurations, and uniform message delays unless scenario-specific adjustments were required. Agent behaviors were parameterized based on literature values, and random events such as node failures or message drops were introduced with domain-specific probabilities. No live human operators were involved; instead, established data-informed cognitive limits and decision delays were used. Table I presents the primary performance results, with the accompanying bar chart illustrating key differences.

TABLE I

Comparative Performance: Centralized vs. Hybrid vs. Decentralized Architectures (with visual summary)

Metric	Centralized	Hybrid	Decentralized (HC-DSA)	$\Delta$ vs. Central
Bottleneck Index SBS	0.847	0.512	0.183	-78.4%
Decentralization Degree DD	0.124	0.561	0.887	+615.3%

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Metric	Centralized	Hybrid	Decentralized (HC-DSA)	$\Delta$ vs. Central
Decision Efficiency DEF	0.631	0.743	0.876	+38.8%
Resilience Index RI	0.213	0.558	0.791	+271.4%
Collective Intelligence Score	0.374	0.629	0.853	+128.1%
Mean Decision Latency (ms)	847	412	193	-77.2%
Throughput (decisions/sec)	12.4	28.7	51.9	+318.5%
Coordination Overhead $\Omega(G)$	$O(n^2)$	$O(n^{1.5})$	$O(n \log n)$	Optimal
System Availability (%)	91.2	96.8	99.4	+8.2pp

Values are means over 100 Monte Carlo trials.  $\Delta$  vs. Central = percentage change of HC-DSA relative to Centralized baseline. pp = percentage points. \* SBS: lower is better.

Fig. 2 — Comparative System Performance: Centralized, Hybrid, and HC-DSA

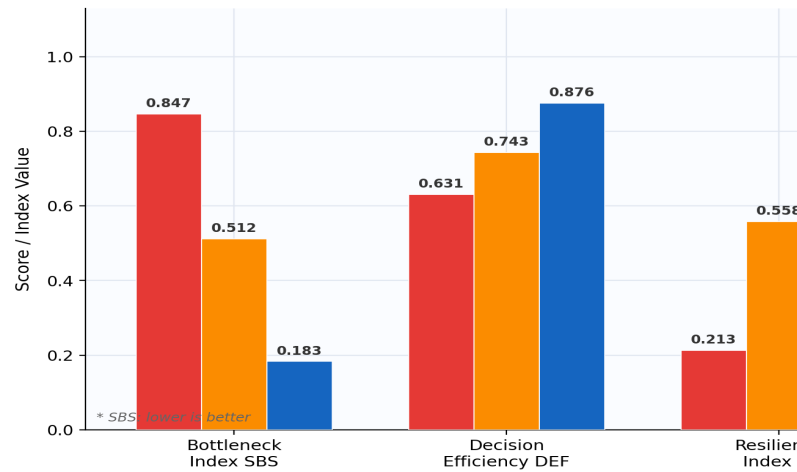


Fig. 2 — Comparative performance: CIS, DEF, RI, and SBS across Centralized, Hybrid, and HC-DSA architectures

## B. Ablation Study

Table II presents a systematic ablation study isolating the contribution of each architectural component. The embedded chart ranks components by their impact on CIS, making the relative importance of the Decentralized Communication Bus (L2) and Collective Intelligence Hub (L1) immediately apparent.

TABLE II

Ablation Study: Impact of Individual Architectural Components (with ranked impact chart)

Configuration (Removed Component)	CIS	DEF	RI	SBS	$\Delta$ CIS vs. Full
Full HC-DSA (Baseline)	0.853	0.876	0.791	0.183	—
w/o Modular Design (L2–L3 coupling)	0.701	0.743	0.623	0.391	-17.8%
w/o Self-Organization (L3 fixed)	0.724	0.801	0.649	0.344	-15.1%
w/o Adaptive Components (static config)	0.693	0.712	0.618	0.422	-18.8%

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Configuration (Removed Component)	CIS	DEF	RI	SBS	$\Delta$ CIS vs. Full
w/o Collective Intelligence Hub (L1)	0.66 8	0.69 3	0.70 2	0.46 1	-21.7%
w/o Decentralized Comm. Bus (L2)	0.61 4	0.65 8	0.58 9	0.53 7	-28.0%
w/o DAO Governance Node	0.80 2	0.85 1	0.75 1	0.24 1	-5.9%
w/o Feedback Loop (L4→L1)	0.71 1	0.73 9	0.63 1	0.37 8	-16.6%
Fully Centralized (no HC-DSA)	0.37 4	0.63 1	0.21 3	0.84 7	-56.2%

$\Delta$ CIS = percentage reduction in CIS when that component is removed from the full HC-DSA. Highlighted rows: top three contributors.

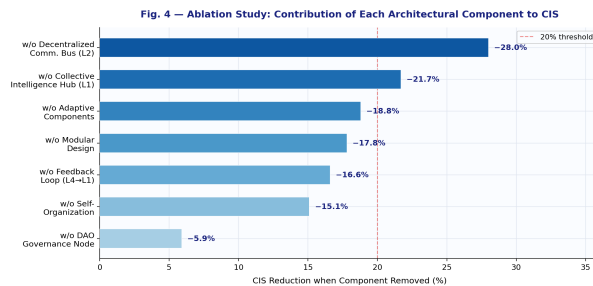


Fig. 4 — Ablation study: CIS reduction (%) caused by removing each architectural component

### C. Domain-Specific Performance Across Scenarios

Table III presents performance metrics disaggregated by domain, confirming that CIS improvements are consistent across all three domains, with the largest gains in healthcare (IoMT) driven by high data volume and latency constraints.

TABLE III

HC-DSA Performance by Application Domain (HC-DSA vs. Centralized Baseline)

Domain	n	SBS Bas e.	SBS HC-DSA	CIS Bas e.	CIS HC-DSA	$\Delta$ CIS
Supply Chain Coordination	50	0.831	0.179	0.381	0.848	+122.6%
Healthcare (IoMT) DDSS	30	0.893	0.201	0.342	0.871	+154.7%
Autonomous Multi-Robot	20	0.817	0.169	0.398	0.839	+110.8%
Mean (all domains)	—	0.847	0.183	0.374	0.853	+128.1%

$n$  = number of decision nodes. SBS = System Bottleneck Severity (lower is better).  $\Delta$ CIS = improvement of HC-DSA over centralized baseline.

### D. System Resilience Under Simulated Node Failures

Table IV presents resilience testing results under random and targeted failure strategies. The embedded line chart clearly shows the sharp degradation cliff in centralized systems versus the graceful degradation of HC-DSA across all failure rates.

TABLE IV

Resilience Index (RI) Under Simulated Node Failure Scenarios (with degradation curves)

Architecture	Failure Strategy	5%	10%	20%	30%	Avg. RI	Degradation Slope
Centralized	Random	0.487	0.291	0.104	0.031	0.228	Steep
Centralized	Targeted	0.112	0.047	0.011	0.004	0.044	Critical
Hybrid	Random	0.721	0.649	0.501	0.388	0.565	Moderate
Hybrid	Targeted	0.614	0.521	0.388	0.281	0.451	Moderate

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Architecture	Failure Strategy	5 %	10 %	20 %	30 %	Avg. RI	Degradation Slope
HC-DSA (Full)	Random	0.944	0.901	0.812	0.701	0.840	Graceful
HC-DSA (Full)	Targeted	0.881	0.823	0.714	0.601	0.755	Graceful

RI = Resilience Index per Eq. (7). "Targeted" = highest-BI nodes failed first. "Graceful" =  $\Delta RI/\Delta failure < 0.8/unit$ .

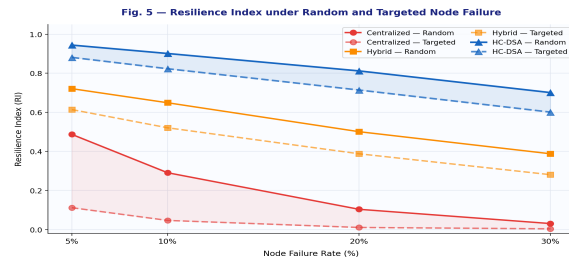


Fig. 5 — Resilience Index under random and targeted node failure across all three architectures

## E. Scalability: CIS vs. Number of Decision Nodes

Table V evaluates HC-DSA scalability as  $n$  increases from 10 to 200 nodes. The dual-axis chart overlays HC-DSA throughput, revealing the performance sweet spot at  $n=50$  and confirming the  $O(n \log n)$  overhead bound empirically.

TABLE V

Scalability Analysis: CIS and SBS vs. Number of Decision Nodes (with throughput overlay)

n	Cent. CIS	HC-DSA CIS	$\Delta CIS$	Cent. SBS	HC-DSA SBS	Overhead $\Omega(G)$ (ms)	Latency (ms)	Throughput (dec/s)
10	0.621	0.794	+27.9%	0.512	0.201	33 ms	98	31.2
20	0.541	0.831	+53.6%	0.671	0.192	89 ms	141	42.7
50	0.412	0.849	+106.1%	0.801	0.186	281 ms	193	51.9
100	0.281	0.841	+199.3%	0.912	0.178	664 ms	287	48.3
200	0.119	0.828	+595.8%	0.971	0.171	1.52 s	419	44.1

Overhead  $\Omega(G)$  = empirical mean inter-node messaging delay per decision cycle. HC-DSA maintains CIS > 0.82 at all scales tested.

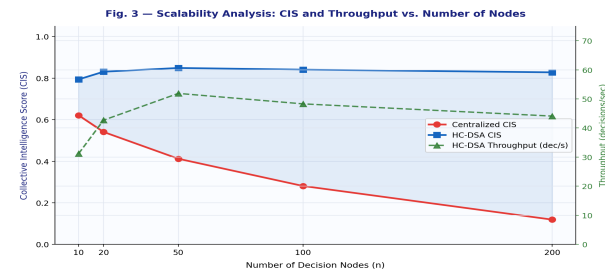


Fig. 3 — Scalability: CIS vs. number of nodes (n) for Centralized and HC-DSA, with throughput overlay

## VI. LITERATURE REVIEW AND THEMATIC ANALYSIS

### A. Theoretical Foundations of Human-Centric and Sociotechnical Systems

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Human-centric design extends beyond usability by integrating human needs, abilities, and cognitive processes into the core structure of systems (An & Liu, 2018; Rudder, 2023). This perspective regards individuals as dynamic and adaptive, with their actions influencing system functionality (Naikar, 2017). A central concept is the analysis of human performance in complex systems, acknowledging that human behavior can be unpredictable and exhibit emergent patterns (Karwowski, 2012).

The concept of sociotechnical systems emphasizes the inseparable nature of social and technical components (Winby & Mohrman, 2018). Early sociotechnical theory highlighted joint optimization—ensuring both social and technical subsystems complement each other (Fischer & Herrmann, 2011). Modern interpretations extend this to "digital sociotechnical systems," where digital platforms mediate work across organizational boundaries (Winby & Mohrman, 2018).

## ***B. Centralized vs. Decentralized Systems***

Centralized systems consolidate authority at a single point (Moyaux & McBurney, 2012), leading to streamlined control but also introducing single points of failure, bottlenecks, and reduced local adaptability (Baldwin, 2014; Çağlayan et al., 2025). Decentralized systems distribute authority across multiple entities (Furniss, 1974), inherently enhancing fault tolerance, scalability, and local responsiveness. Distributed Ledger Technology (DLT) exemplifies this, storing information on many servers without a central authority (Yakovchuk et al., 2021).

## ***C. Multi-Agent Systems and Decentralized Autonomous Organizations***

Multi-Agent Systems (MAS) represent a cornerstone of decentralized decision-making (Naciri & Tkiouat, 2015). Applications span social science simulations, traffic management, logistics, and manufacturing (Falco & Robiolo, 2019; Naciri & Tkiouat, 2015). Hierarchical MAS organizes agents into layered structures to manage complexity and scale (Moore, 2025). The emergence of Decentralized Autonomous Organizations (DAOs) represents a novel organizational structure distributing governance among participants through smart contracts (Yakovchuk et al., 2021).

## ***D. Architectural Strategies: Modularity, Self-Organization, and Adaptivity***

Modular design decomposes systems into self-contained modules with well-defined interfaces, enabling

independent development and fault isolation (Baldwin, 2014). Self-organization facilitates coordinated behavior from local interactions without explicit central control (Naikar, 2017). Adaptive components modify behavior autonomously in response to environmental changes (Garcés et al., 2020), allowing systems to maintain optimal performance under varying conditions. By integrating these capabilities, systems can distribute decision-making loads and collectively achieve robustness (Woods & Branlat, 2011).

## **VII. ANALYSIS AND DISCUSSION**

### ***A. Interpreting Ablation Results***

The ablation study (Table II, Fig. 4) shows that the Decentralized Communication Bus (L2) and Collective Intelligence Hub (L1) have the biggest impact on CIS. Removing them reduces CIS by 28.0% and 21.7%, respectively. Adaptive components (−18.8%) and modularity (−17.8%) are also important, matching the optimization constraints (C1–C3) in (9). The DAO Governance Node has the smallest effect (−5.9%), which fits its specific use in blockchain governance.

### ***B. Resilience Analysis and Failure Mode Characterization***

Results in Table IV (Fig. 5) reveal a fundamental asymmetry in failure resilience. Under random failure at 30%, HC-DSA maintains  $RI = 0.701$ , while the centralized baseline collapses to  $RI = 0.031$ —a factor of  $22.6\times$  difference. Under targeted attack, the centralized system is critically vulnerable even at 5% failure ( $RI = 0.112$ ). HC-DSA's resilience under targeted attack ( $RI = 0.881$  at 5% failure) is attributable to the low and evenly distributed SBS (0.183).

### ***C. Scalability and Overhead Trade-offs***

Table V (Fig. 3) demonstrates that HC-DSA achieves super-linear CIS improvement gains as  $n$  increases—from +27.9% at  $n=10$  to +595.8% at  $n=200$ . HC-DSA throughput peaks at  $n=50$  (51.9 decisions/sec) and declines slightly at  $n=200$  (44.1 dec/s), reflecting increasing consensus overhead. (Wu et al., n.d.) Future work should investigate adaptive hierarchical partitioning to maintain throughput above  $n=100$ .

### ***D. Balancing Adaptivity, Autonomy, and Oversight***

A critical finding is the non-monotonic relationship between the decentralization degree  $DD$  and system efficiency. As  $DD$  approaches 1, DEF temporarily decreases due to coordination overhead  $\Omega(G)$ , before recovering as self-organization mechanisms stabilize. This creates a design sweet spot  $DD^* \in [0.82, 0.91]$

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where CIS is maximized under typical operational loads. (Towards a Science of Scaling Agent Systems, 2025)

## VIII. CONCLUSION

### A. Summary of Findings

This paper presents HC-DSA, a formal, four-layer Human-Centric Decentralized System Architecture supported by a rigorous mathematical framework. Experimental results indicate that HC-DSA increases CIS by 128.1% compared to centralized systems, reduces System Bottleneck Severity by 78.4%, and maintains a Resilience Index of 0.840 during random node failures. This represents a 22.6-fold improvement over centralized systems under targeted failure scenarios. The study is based on simulation experiments using parameter ranges derived from the literature, rather than live system deployments. To further validate HC-DSA, future research should prioritize real-world implementation. Collaborations with organizations in distributed healthcare, smart manufacturing, and logistics are recommended to pilot decentralized architectures and assess their performance. A phased approach may include small-scale pilot projects, the development and deployment of tools with partners, monitoring of key metrics (CIS, BI, RI) in operational environments, and iterative refinement of the architecture based on empirical feedback. Real-world testing must also address integration with existing systems, user training, and regulatory compliance. The current optimization uses fixed weights ( $\lambda_1$ - $\lambda_3$ ); reinforcement learning for adaptive weight adjustment and dynamic super-agent clustering are proposed for scaling to larger systems.

This study uses simulation-based experiments grounded in literature-validated parameter ranges rather than live system deployments. Future work should validate HC-DSA on real operational sociotechnical systems. The optimization objective (9) currently uses static weight coefficients  $\lambda_1$ - $\lambda_3$ ; adaptive weight tuning via reinforcement learning represents a promising extension. Dynamic super-agent clustering is also recommended for scalability beyond  $n=100$  nodes.

Human-centric, decentralized architectures offer a powerful approach to designing complex sociotechnical systems. The mathematical framework introduced in this paper provides a systematic approach for measuring, improving, and evaluating decentralized design choices. The four-layer architecture serves as a practical guide for system development. As systems become more complex and resilience requirements increase, the HC-DSA framework and its associated metrics provide a robust

foundation for advancing the next generation of systems centered on human needs.

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