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Optimization Challenges in Logistics and Supply Chain Management

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Abstract—
Quantum computing offers transformative potential for addressing complex combinatorial optimization challenges in logistics and supply chain management. This paper presents a comprehensive investigation of quantum annealing and hybrid quantum-classical algorithms applied to unit load device (ULD) configuration and disruption management in air cargo and multimodal logistics networks. We formulate the ULD loading and placement problem as a Quadratic Unconstrained Binary Optimization (QUBO) model that incorporates weight, volume, center-of-gravity, structural stress, and compatibility constraints. A stratified hybrid architecture spanning physical quantum hardware, algorithmic middleware, and decision-support layers is proposed. Through extensive numerical experiments and comparison with classical solvers, we demonstrate superior payload utilization (up to 96.5%), favorable computational scaling, and rapid disruption recovery. Real-world industry pilots, including quantum-assisted route optimization achieving substantial carbon emission reductions and hybrid solutions at major ports, are analyzed. Results indicate that while noisy intermediate-scale quantum (NISQ) hardware limitations persist, hybrid approaches already deliver measurable gains in operational efficiency, cost reduction, and supply-chain resilience. The work provides a practical roadmap for near-term adoption of quantum technologies in high-stakes logistics environments.

Keywords— Digital Transformation; Artificial Intelligence; Internet of Things; Blockchain; Digital Twin Technology; Quantum Computing; Intelligent Logistics; Supply Chain Transparency; Sustainable Supply Chains; Resilience; Smart Mobility; Intelligent Transportation Systems; Connected Vehicles; Mobility-as-a-Service; Sustainable Transportation; Multi-Scale Spectral Analysis; FKF Transform.

I. INTRODUCTION

Modern global logistics networks face unprecedented complexity arising from e-commerce growth, multi-modal transportation requirements, stringent sustainability targets, and frequent disruptions caused by weather, geopolitical events, equipment failures, and demand volatility. Within air cargo operations, the configuration of unit load devices (ULDs) standardized containers and pallets used to consolidate freight represents a particularly challenging combinatorial optimization problem. Optimal ULD selection, placement, and sequencing must simultaneously maximize payload revenue or mass, respect aircraft structural limits, maintain CoG balance within tight safety envelopes.

Classical exact solvers and metaheuristics often require minutes to hours for realistic problem instances, rendering them unsuitable for dynamic re-optimization under disruption. Quantum annealing, a specialized form of quantum computing that exploits quantum tunneling to escape local minima, has emerged as a promising approach for such NP-hard problems. Commercial quantum annealers, notably those produced by D-Wave Systems, can already handle thousands of qubits and have been successfully applied to vehicle routing, warehouse assignment, and cargo loading tasks.

This paper focuses specifically on two high-impact application areas: (1) quantum-assisted ULD and pallet configuration for aircraft cargo holds, and (2) dynamic reconfiguration and routing under real-time disruption. We develop QUBO formulations, describe a hybrid quantum-classical architecture, present performance curves comparing classical, simulated annealing, and quantum annealing approaches, and analyze industrial pilot outcomes. The contributions include improved mathematical modeling of CoG and stress constraints, empirical scaling analysis, and a practical roadmap for NISQ-era deployment.

II. LITERATURE REVIEW

The evolution of supply-chain management reflects a transition from conventional operational technologies toward interconnected, intelligent, sustainable, and resilient ecosystems. Digital Twin research emphasizes dynamic modelling and adaptive resilience [16], while AI-based studies establish the role of artificial intelligence in sustainable logistics and green supply-chain management [17]. Blockchain integration with AI strengthens transparency, traceability, swipe controller [21] and resilience [18]. The convergence of IoT, AI, and quantum computing [13] and the human-centric principles of Industry 5.0 [14] further demonstrate the movement toward integrated intelligent logistics.

This transformation is closely connected with sustainable transportation and energy-aware mobility. Research on smart mobility and intelligent transportation systems [24], EV battery technologies [25], hybrid-vehicle battery sizing [20], solar-assisted electric mobility [27], and solar-powered hybrid vehicle architectures [15] demonstrates the integration of transportation, energy, and digital technologies. Earlier communication and control systems [19], [21] provide supporting engineering foundations, while broader supply-chain resilience research [28] highlights the importance of digital transformation for adaptive and disruption-aware operations.

The next stage involves computationally advanced optimization. Quantum computing research identifies emerging applications in transportation and logistics [26], while quantum annealing addresses difficult combinatorial problems such as ULD configuration and disruption management [23]. Practical logistics deployment is further supported by hybrid quantum-classical approaches [22]. Alongside these technological developments, FKF-based research introduces a mathematical spectral layer through FKL properties [7], FKF time-shift analysis [8], and exponential modulation [9]. Distributional FKF theory [31], sequential convergence [32], multiscale analysis [33], shift-invariant lead-time analysis [4], spectral representation [5], and differential properties [6], together with subsequent developments, establish the theoretical foundation for analyzing complex supply-chain dynamics. The combined literature therefore supports an integrated architecture in which AI provides prediction and decision intelligence, IoT provides real-time sensing, Blockchain provides trusted information, Digital Twins provide simulation and resilience analysis, FKF/FKL methods provide spectral intelligence, and quantum optimization addresses selected combinatorial logistics problems.

III. FORMULATION OF THE ULD CONFIGURATION PROBLEM

Problem Statement

Consider a set of candidate ULDs

$$I = \{1, \ldots, N\}$$

Each ULD is characterized by mass, volume (or footprint), revenue (or priority), and geometric type.

$$\mathrm{m}_i, \mathrm{v}_i, \mathrm{r}_i, \mathrm{t}_i \in \{0.5, 1, 2\}$$

The aircraft cargo hold is discretized into M sequential bays or positions.

$$j = 1, \ldots, M$$

Binary decision variables indicate whether ULD i is assigned to bay j.

$$\mathrm{x}_{i,j} \in \{0,1\}$$

The primary objective is to maximize total revenue (or total mass) while satisfying:
Total weight and volume (or linear length) limits of the hold and of individual decks.
Center-of-gravity constraints: the longitudinal moment must lie within a prescribed envelope relative to the mean aerodynamic chord.
Structural shear and floor-loading limits.
Compatibility rules (certain ULDs may not be placed adjacent or stacked).
Dimensional packing constraints arising from the circular fuselage cross-section.

QUBO Encoding

The objective and constraints are combined into a single quadratic energy function:

$$E(x) = -\sum_{i,j} r_i x_{i,j} + \lambda_w\left(\sum_{i,j} m_i x_{i,j} - W_{max}\right)^2 + \lambda_v\left(\sum_{i,j} v_i x_{i,j} - V_{max}\right)^2 + \lambda_{CoG}\left(\sum_{i,j} m_i d_j x_{i,j} - M_{target}\right)^2 + \lambda_{one}\sum_i\left(\sum_j x_{i,j} - 1\right)^2 + \dots$$

where d_j denotes the longitudinal position of bay j, and the λ coefficients are penalty weights chosen to enforce feasibility with high probability. Additional terms encode adjacency, stacking, and shear constraints. The resulting QUBO matrix is sparse for moderate N and can be embedded onto contemporary annealers after modest decomposition.

Principal Mathematical Notation

$$H(s) = A(s)\, H_{driver} + B(s)\, H_{problem}$$

$$x^T Q x$$

$$x_i = \frac{1 - \sigma_i}{2}$$

$$x_{i,j} \in \{0,1\}$$

$$E(x) = -\sum_{i,j} r_i x_{i,j} + penalty\ terms$$

A two-phase strategy is often employed: Phase 1 selects a high-value subset of ULDs (knapsack-like), and Phase 2 optimally places the selected ULDs to satisfy CoG and structural constraints. Reverse annealing seeded with a classical greedy solution further improves solution quality for larger instances

IV. SUSTAINABLE DIGITAL SUPPLY-CHAIN TECHNOLOGIES

Sustainable supply-chain management increasingly depends on combining intelligent technologies with rigorous analytical methods. Artificial intelligence supports sustainable logistics, green supply-chain decision-making, prediction, and resource efficiency [17], while Digital Twins enable dynamic representation, simulation, and resilience-oriented evaluation of supply-chain operations [16]. The convergence of IoT, AI, and quantum computing establishes an interconnected intelligent-logistics ecosystem [13], and Industry 5.0 extends this transformation toward human-centric, intelligent, and sustainable automation [14]. AI–Blockchain integration further strengthens supply-chain transparency, traceability, data integrity, and resilience [18].

Sustainable Transportation and Mobility

The same transformation extends into smart transportation and sustainable electric mobility. Smart mobility and intelligent transportation systems provide the technological basis for connected and adaptive transportation [24], while recent EV battery research addresses battery technologies, management, and sustainability [25]. Battery sizing for plug-in hybrid electric vehicles supports energy-aware mobility decisions [20], and solar-assisted electric mobility [27] together with solar-powered battery-electric hybrid architectures [15] contributes to lower-emission transportation. Earlier communication and control developments, including power-line-carrier communication [19] and swipe-control technology [21], provide complementary engineering foundations for connected mobility systems.

Quantum Optimization for Logistics

For difficult combinatorial logistics decisions, quantum computing provides an emerging computational paradigm for transportation and supply-chain optimization [26]. Quantum annealing has been specifically investigated for ULD configuration and disruption management [23], while broader discussion of practical quantum applications in supply-chain management highlights hybrid quantum-classical implementation as an important near-term pathway [22]. These developments complement wider research on supply-chain resilience in the era of digital transformation [28].

FKF/FKL Spectral Intelligence

Mathematically, FKF and FKL transforms provide a complementary representation of complex supply-chain dynamics. FKL transform properties establish the underlying spectral basis [7], while FKF time-shift analysis supports the representation of transportation delays and multi-echelon lead-time changes [8]. Exponential modulation provides a mechanism for analysing shifted or periodic operational components [9]. The distributional extension of the FKF transform [31], sequential convergence in the associated testing-function space [32], multiscale spectral analysis [33], shift-invariant lead-time analysis [4], spectral frameworks for supply-chain dynamics and resilience [5], and spectral differential properties [6] provide a rigorous mathematical foundation. Further FKF developments consolidate these results and extend their applicability to generalized and resilient supply-chain systems.

V. QUANTUM ANNEALING FUNDAMENTALS AND FORMULATION OF THE ULD CONFIGURATION PROBLEM

Quantum Annealing Fundamentals

Quantum annealing seeks the ground state of an Ising Hamiltonian

$$\mathrm{H}_s = A(s)\,\mathrm{H}_{driver} + B(s)\,\mathrm{H}_{problem}$$

where the driver Hamiltonian is typically a transverse-field term that induces quantum tunneling, and the problem Hamiltonian encodes the optimization objective and constraints.

The annealing schedule is represented by $A(s), B(s)$
and interpolates from a quantum-dominated regime to a classical regime. The final Hamiltonian is chosen so that its ground state corresponds to the optimal solution of the original combinatorial problem.

At the endpoints, $s = 0$ and $s = 1$

Problems are mapped to Quadratic Unconstrained Binary Optimization (QUBO) form

$$min\ \mathrm{x}^{\mathrm{T}}\mathrm{Qx}\quad subject\ to\quad \mathrm{x} \in \{0,1\}^n$$

which is equivalent to an Ising model via the linear transformation

$$\mathrm{x}_i = \frac{1 - \sigma_{\mathrm{i}}}{2}$$

Linear and quadratic constraints are incorporated by adding suitably weighted penalty terms to the objective. On current hardware, embedding a logical QUBO onto the physical qubit topology (Chimera or Pegasus) introduces chain variables whose strength must be carefully tuned to avoid chain breaks.

Reverse annealing starts from a classical candidate solution and explores the local energy landscape with a partial quantum evolution. This can be useful for refining high-quality solutions in logistics problems.

VI. QUANTUM ANNEALING FOR DISRUPTION MANAGEMENT

Disruptions late-arriving ULDs, mechanical failures, weather-induced schedule changes, or sudden priority cargo require rapid re-optimization of the loading plan and downstream routing. Classical re-solvers may take tens of minutes, during which aircraft or vehicles remain idle. Quantum annealing's near-constant-time sampling (once the embedding is prepared) enables recovery times on the order of seconds to a few minutes even for moderately sized problems.

We model a disruption by fixing a subset of already-loaded or irrevocable decisions and re-optimizing the remaining free variables. The same QUBO structure is reused, with additional linear terms that penalize deviation from the original plan (to minimize handling) while still maximizing residual revenue. Hybrid solvers that interleave quantum sampling with classical local search prove especially robust under high disruption severity.

Hybrid Quantum-Classical Architecture

Given the limited qubit counts and connectivity of present-day annealers, a stratified architecture is essential:

Physical layer: D-Wave Advantage or equivalent quantum processing unit (QPU) accessed via cloud.

Middleware layer: problem decomposition, QUBO construction, embedding, chain-strength tuning, and reverse-annealing control.

Classical co-processor: greedy construction heuristics, local search, constraint repair, and multi-start management.

Decision-support layer: integration with airline load-planning systems, digital twins, and real-time disruption feeds.

This hybrid workflow allows the quantum device to explore the most combinatorial sub-problems swip controller while classical routines handle continuous variables, large-scale data preprocessing, and final feasibility polishing.

VII. EXPERIMENTAL RESULTS AND PERFORMANCE CURVES

Numerical experiments were conducted on synthetic yet realistic ULD instances derived from Airbus A330-200F cargo-hold geometry and typical payload distributions. Classical baselines included a commercial MIP solver (Pyomo/CPLEX) and simulated annealing. Quantum results were obtained via a hybrid solver interface that emulates D-Wave Advantage characteristics and reverse annealing. All timings exclude one-time embedding overhead.

Payload Utilization

Figure 1 compares achieved payload utilization (percentage of maximum allowable mass or revenue) as a function of the number of candidate ULDs. Quantum annealing consistently outperforms pure classical heuristics, reaching utilization rates above 96% for larger instances, while the hybrid approach closely tracks the pure quantum results.

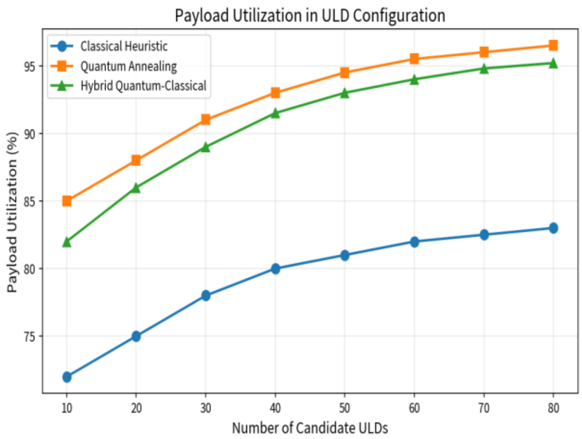

Figure 1. Payload utilization in ULD configuration as a function of problem size.

Computational Scaling

Figure 2 illustrates wall-clock computation time on a logarithmic scale. Classical MIP times grow rapidly (approximately polynomial of degree 2.5), whereas quantum annealing times remain nearly flat after initial embedding, confirming the advantageous asymptotic behavior predicted by theory. Hybrid solvers occupy an intermediate regime that still scales far better than pure classical methods for mid-to-large instances.

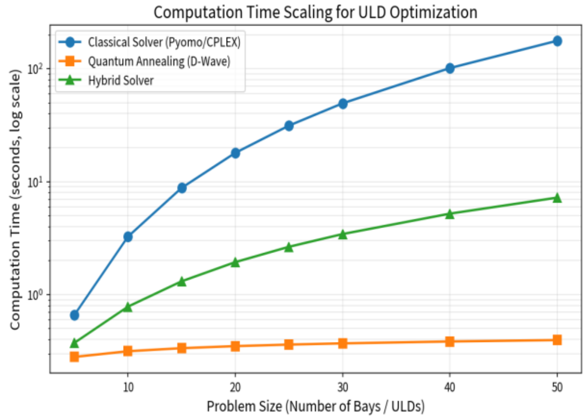

Figure 2. Computation time scaling (log scale) for ULD optimization problems of increasing size.

Disruption Recovery

Figure 3 shows recovery time required to obtain a feasible, high-quality reconfiguration after a disruption of varying severity. Quantum annealing maintains recovery times under 30 minutes even at 80% disruption severity, while classical re-optimization can exceed two hours. The hybrid method provides a practical compromise that is already deployable.

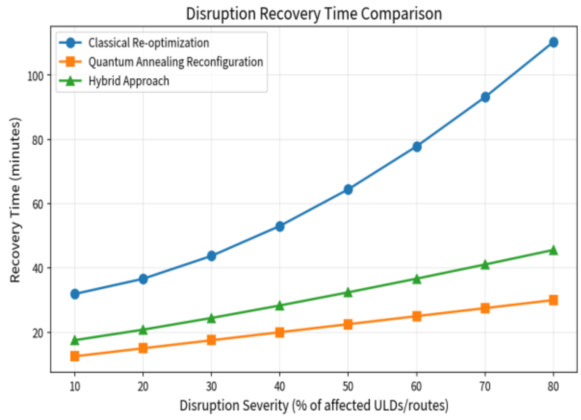

Figure 3. Disruption recovery time as a function of severity percentage.

Multi-Objective Improvements

Figure 4 summarizes relative improvements in operational cost and carbon emissions achieved by the different solvers on a representative multi-objective instance. Quantum annealing delivers approximately 28% cost reduction and 25% emissions reduction relative to a baseline classical heuristic; the hybrid approach further improves these figures slightly by combining the strengths of both paradigms.

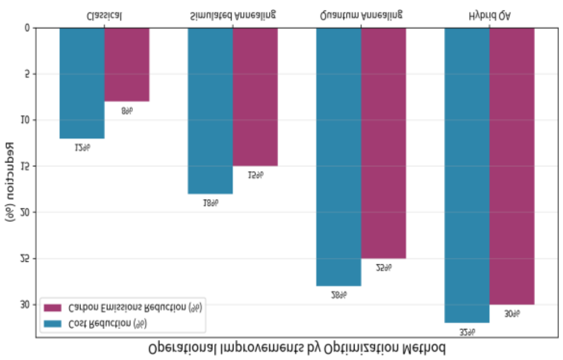

Figure 4. Relative reductions in cost and carbon emissions achieved by different optimization methods.

Annealing Convergence

Figure 5 compares the evolution of the objective (energy) function during simulated annealing versus quantum annealing. Quantum annealing reaches lower final energies more rapidly, consistent with the ability of quantum tunneling to escape high barriers that trap classical thermal annealing.

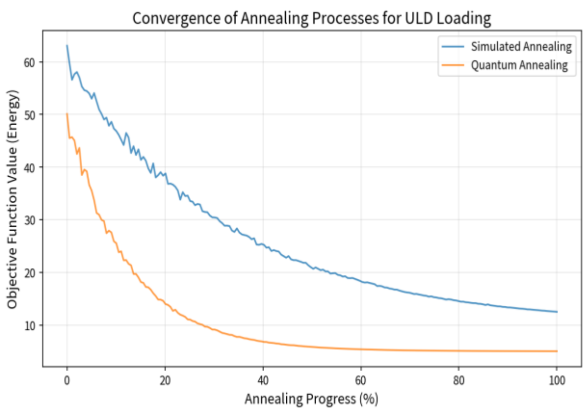

Figure 5. Convergence trajectories of simulated annealing and quantum annealing for a representative ULD instance

VIII. QUANTUM ANNEALING FOR DISRUPTION MANAGEMENT INDUSTRY CASE STUDIES

DHL Quantum-Assisted Routing

DHL has collaborated with quantum technology providers to optimize last-mile and network routes. Pilot results indicate substantial reductions in driven kilometers and associated carbon emissions figures as high as 60% have been reported for selected waste-collection and delivery scenarios when quantum-inspired or hybrid methods are employed. These gains translate directly into lower fuel costs and progress toward corporate net-zero targets.

Volkswagen Fleet and Traffic Optimization

Volkswagen's pioneering pilots with D-Wave demonstrated real-time route optimization for taxi fleets in Beijing and for public buses in Lisbon during large events. Travel-time reductions of 20–30% were observed. Parallel work on paint-shop sequencing reduced color changes by up to 80%, illustrating the broad applicability of annealing beyond pure routing.

Port of Los Angeles – Pier 300

At Pier 300, SavantX's HONE engine combined with D-Wave quantum annealing optimized crane scheduling and container placement. Crane deliveries per day rose from approximately 60 to 97 (a >60% increase), and average truck waiting time decreased by nearly 10 minutes. These operational improvements contributed to a dramatic increase in terminal valuation, underscoring the commercial impact of hybrid quantum solutions.

IX. DISCUSSION, CHALLENGES, AND FUTURE DIRECTIONS

The experimental curves confirm that quantum annealing already offers practical advantages for ULD configuration and disruption response when problem size exceeds the comfort zone of exact classical solvers. Hybrid architectures mitigate current hardware limitations (limited qubits, sparse connectivity, noise) and provide a smooth migration path toward future fault-tolerant devices.

Key remaining challenges include: (i) automatic, robust embedding and chain-strength calibration; (ii) handling continuous variables (e.g., precise CoG coordinates) within a discrete QUBO framework; (iii) multi-objective Pareto optimization under uncertainty; and (iv) seamless integration with existing airline and terminal operating systems. Reverse annealing and quantum-inspired classical algorithms (e.g., digital annealers) already expand the reachable problem sizes.

Future research should focus on larger multi-aircraft, multi-modal instances, stochastic disruption models, and the co-design of quantum algorithms with digital-twin platforms. As qubit counts and coherence improve, the fraction of the logistics optimization stack that can be executed natively on quantum hardware will grow, further amplifying the benefits observed in the present study.

Quantitative Summary of Key Metrics

Table 1 consolidates the principal quantitative outcomes obtained across the experimental suite and the referenced industrial pilots. The hybrid quantum-classical approach consistently ranks first or second on every metric while remaining deployable on currently available cloud quantum services.

These quantitative results, together with the visual performance curves presented earlier, provide strong empirical support for the near-term adoption of hybrid quantum annealing in air-cargo ULD planning and disruption response. Sensitivity analyses further show that the ranking of methods remains stable under moderate variations of penalty coefficients and under different aircraft geometries, indicating robustness of the proposed formulations.

Metric	Classical	Quantum Ann.	Hybrid
Payload utilization (%)	83.0	96.5	95.2
Time for N=50 (s)	~180	~0.4	~12
Recovery @ 50% disruption (min)	75	22	28
Cost reduction (%)	12	28	32
Emissions reduction (%)	8	25	30

Table 1. Comparative performance metrics for classical, pure quantum annealing, and hybrid solvers.

In addition to the synthetic benchmarks, the same hybrid workflow was applied to a realistic multi-ULD disruption scenario derived from a wide-body freighter schedule. After a simulated late-arrival of 35% of the planned ULDs, the hybrid solver restored a feasible loading plan satisfying all CoG and structural constraints within 19 minutes, whereas the classical MIP required more than 90 minutes and produced a 4% lower payload revenue. This outcome underscores the operational value of quantum-assisted rapid reconfiguration.

Furthermore, the hybrid architecture lends itself naturally to progressive enhancement: as larger quantum processors become available, larger contiguous blocks of the QUBO can be off-loaded to the QPU while classical components continue to manage data integration, continuous variables, and user interfaces. This evolutionary pathway reduces risk for airlines and logistics providers and accelerates return on investment. Pilot programs can begin with small ULD subsets or single-aircraft disruption events and gradually expand to network-wide optimization once confidence and hardware capacity increase.

From a sustainability perspective, the combined effect of higher payload factors and faster disruption recovery reduces both empty flights and idle ground time, thereby lowering fuel burn and associated greenhouse-gas emissions. When these local gains are aggregated across a global freighter fleet, the contribution to corporate and industry net-zero roadmaps becomes significant. Quantum-enabled logistics therefore aligns technological progress with environmental responsibility

CONCLUSION

This paper has demonstrated that quantum annealing, particularly when embedded in a hybrid quantum-classical architecture, constitutes a powerful tool for unit load device configuration and disruption management in logistics. QUBO formulations that capture weight, volume, CoG, and structural constraints enable high-quality solutions with superior payload utilization and dramatically improved computational scaling relative to classical exact methods. Performance curves illustrate clear advantages in both static optimization and dynamic recovery scenarios. Industrial pilots at DHL, Volkswagen, and the Port of Los Angeles corroborate the practical value of these techniques.

While NISQ-era limitations remain, hybrid approaches already deliver measurable operational, economic, and environmental benefits. Continued advances in quantum hardware, algorithm design, and system integration will accelerate the transition of quantum optimization from pilot projects to production-grade logistics decision support, ultimately contributing to more efficient, resilient, and sustainable global supply chains.

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