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Designing a Blockchain-Based Supply Chain Risk Management Model Using a Genetic Algorithm (Case Study: Dairy Industries of Gilan Province)

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ABSTRACT

With the expansion of competition and the growing complexity of supply chains—especially in quality-sensitive food industries such as dairy products—the need for innovative approaches to simultaneously manage cost and risk has become increasingly critical. The present study employed a quantitative and applied research method, and data were collected through fieldwork and official statistical sources. The genetic algorithm was implemented with an initial population of 50 chromosomes and 100 generations, incorporating uniform crossover, binary and real-valued mutations, and local search through the genetic algorithm method. In this research, a three-tier supply chain model was designed for the dairy industry of Gilan Province, including suppliers, industrial and traditional production units, and consumer markets, which was optimized using the genetic algorithm. The objective function of the model was to minimize the combined total cost and supply risk with respective weights of 0.7 and 0.3, while the constraints included supplier capacity, production capability of workshops, and full demand satisfaction. Real-world data on capacity, price, transportation cost, and risk indices from three major suppliers were used as model inputs. Simulation of the genetic algorithm with a population of 50 chromosomes and 100 generations showed that the algorithm rapidly reduced costs during the initial generations and gradually converged around generation 80. The final results indicated that the model achieved an optimal total cost of 454,101,315 tomans and an overall risk of 4.87%, with an allocation pattern in which supplier S3 had the largest share, S2 a moderate share, and S1 the smallest share to control risk. This multi-supplier solution effectively balanced cost and risk, and it can be practically applied as a basis for strategic decision-making in the dairy supply chain.

Keywords: *Supply Chain Risk Management, Blockchain, Genetic Algorithm, Dairy Products.*

1. Introduction

Global supply chains have entered a period of persistent turbulence marked by geopolitical shocks, regulatory flux, and technology-driven restructuring, with food and dairy networks particularly exposed because perishability, traceability, and safety requirements magnify operational fragilities (Bednarski et al., 2025). While classic supply chain management emphasizes end-to-end coordination of flows, capacities, and information, today's digitized ecosystems demand architectures that are simultaneously resilient, transparent, and analytically adaptive across multi-tier networks (Hugos, 2024; Tiwari et al., 2024). Perishable food systems—milk collections, processing plants, and downstream markets—face "ripple effects" when upstream disruptions propagate through time-sensitive inventories and temperature-controlled logistics; designing for resilience therefore requires integrated risk management that is data-rich, automation-ready, and auditable across organizational boundaries (Al Aziz et al., 2025; Ngo et al., 2024). Against this backdrop, blockchain platforms coupled with advanced optimization and analytics have emerged as promising enablers to align incentives, codify process rules, and create trusted event histories that support both operational control and strategic governance in agri-food value chains (Chang et al., 2022; Dutta et al., 2020; Vu et al., 2023).

In perishable chains, traceability is not merely a compliance artifact but an economic capability that reduces recall scope, accelerates root-cause analysis, and enables premium pricing through verifiable provenance. Empirical and design-science studies across food categories—dairy included—show that distributed ledgers can encode product histories, quality attributes, and custody transfers in a tamper-evident way, thereby enhancing visibility for regulators, brands, and consumers (Fang & Stone, 2021; Rogerson & Parry, 2020). Use cases in milk and dairy demonstrate how blockchain can synchronize farm collection, cold-chain events, and processing controls with downstream retail audits; industry pilots in India, for example, embed safety and traceability requirements into a shared platform that spans cooperatives and processors (Khanna et al., 2022; Kumar & Kumar, 2023; Vincent et al., 2022). Yet value capture depends on aligning technical choices with governance design: platform permissioning, data standards, and incentive mechanisms must fit sector structures—cooperatives, private processors, and municipal health authorities—without imposing prohibitive adoption costs (Bai & Sarkis, 2020; Mohammadi Fateh & Salarnejad, 2022).

The strategic case for blockchain strengthens when it is integrated with broader digital transformation agendas—electronic data interchange for transactional efficiency, big-data analytics for predictive risk sensing, and cyber-physical automation under Industry 4.0—so that ledgers become part of a composable digital operations backbone rather than an isolated pilot (Jha et al., 2025; Jiang et al., 2024; Khan & Emon, 2025). Recent evidence shows that supply chain integration combined with advanced analytics capabilities improves resilience by enabling faster detection of demand-supply mismatches and capacity bottlenecks; immutable event data from blockchain can feed these models to reduce data latency and reconcile cross-firm records (Jiang et al., 2024; Rashid et al., 2024). In parallel, sectoral studies highlight how supply chain configuration choices shape productivity and sustainability outcomes, reinforcing that digital infrastructures must be co-designed with network structures, asset locations, and collaboration patterns (Lin & Zhu, 2025; Tiwari et al., 2024). For agri-food specifically, bibliometric and conceptual mappings chart a rapid expansion of themes—from smart contracts and IoT sensing to platform governance and sustainability metrics—signaling both opportunity and fragmentation that research needs to synthesize (Kumar & Sahoo, 2025; Mangla et al., 2022; Marouti Sharif Abadi et al., 2024).

Risk management remains central. Logistics 4.0 introduces new cyber-operational risks alongside traditional shortage, quality, and transport uncertainties; here, blockchain's auditability can mitigate certain information and coordination risks, while optimization and simulation provide design-time tools for inventory positioning, sourcing diversification, and contingency routing (Kodym et al., 2020; Rodríguez-Espíndola et al., 2020). In dairy logistics ecosystems, proposed architectures connect farms, coolers, processing lines, and retailers via IoT sensors whose hashed events anchor temperature and handling proofs on a ledger, supporting rapid exception management and targeted recalls (Fang & Stone, 2021). Comprehensive reviews confirm that blockchain's main operational contributions include traceability, authenticity verification, and near-real-time visibility; nonetheless, interoperable data models and cost-justified consensus protocols remain open challenges (Chang et al., 2022; Dutta et al., 2020; Vu et al., 2023). Technology appraisal frameworks therefore recommend evaluating blockchain as part of a portfolio of transparency technologies—APIs, event streaming, digital twins—guided by supply chain criticality and sustainability priorities (Bai & Sarkis, 2020).

From a platform engineering lens, selection among blockchain stacks (e.g., permissioned vs. public, smart-contract expressiveness, throughput constraints) should be decision-analytic. Multi-criteria techniques under uncertainty—such as picture fuzzy compromise ranking—offer structured ways for logistics firms to balance performance, security, scalability, and cost in choosing blockchain platforms (Rani et al., 2025). As adoption scales, smart contracts can operationalize service-level agreements, quality gates, and payment triggers, while discrete-event simulation allows organizations to experiment with contract logic and network latencies before deployment (Jahaniyan & Kiani, 2024). In the Iranian context, conceptual models of blockchain-based supply chain financing emphasize governance, regulatory fit, and the design of data-sharing consortia aligned with domestic financial infrastructure, illuminating pathways for sectoral rollout (Aein & Noori, 2024). Complementary studies during crisis logistics underline the need to identify and prioritize risk factors—transport access, supplier reliability, facility readiness—using integrated fuzzy methods, which can be combined with blockchain evidence records to support faster, more credible crisis decisions (Asghari et al., 2025).

Operational analytics enrich these architectures. Genetic algorithms and machine learning hybrids are increasingly used to navigate high-dimensional supply, production, and distribution decisions under cost-risk trade-offs; these metaheuristics can search allocation policies while learning from ledger-backed data streams that encode supplier reliability and logistics performance (Chawuthai et al., 2025). In parallel, reinforcement learning is gaining traction for dynamic control—inventory policies, routing under stochastic lead times, and adaptive sourcing—where trusted, time-stamped state variables from blockchain improve feedback quality and policy evaluation (Rolf et al., 2023). Such algorithmic controllers should be framed within digitization programs that redesign information flows, roles, and incentives across partners; educational and entrepreneurial perspectives stress building managerial literacy in operations analytics and platform thinking to avoid “technology-first” pitfalls (Jaboob et al., 2024; Tiwari et al., 2024).

Food safety and sustainability elevate the stakes. Modeling studies show that blockchain can reduce the social and economic costs of contamination events by narrowing recall sets and accelerating traceability queries; when combined with simulation, firms can quantify the value of different data-sharing policies and sensor coverage levels (Ma et al., 2024). Circular economy transitions—for example, batteries—illustrate how ecosystem-level data architectures orchestrate many-to-many actors and extended product life cycles; lessons translate to dairy in the form of reusable packaging, waste valorization, and carbon accounting that require standardized, verifiable data exchanges (Chen et al., 2025). Sustainability-related risks (e.g., environmental non-compliance, labor issues) also influence performance; dynamic supply chain management practices, when coupled with immutable records and responsive analytics, help firms both detect and mitigate these exposures (Ngo et al., 2024). At the same time, societal shifts in digital inclusion alter demand patterns and information access, which means consumer-facing traceability portals can reinforce trust and reshape purchasing behavior if designed for accessibility and credible disclosure (Ye & Yue, 2024).

Sectoral evidence underscores both promise and barriers. Tea, coffee, and other agri-commodities demonstrate how blockchain platforms can empower smallholders through verifiable claims and improved bargaining positions, provided platform governance ensures fair data rights and value distribution (Agnola et al., 2025; Mangla et al., 2022). In dairy, blockchain-enabled smart supply chains align with ongoing digital transformations in agribusiness, but scaling requires training, cooperative engagement, and integration with existing ERP/EDI backbones (Jha et al., 2025; Kumar & Kumar, 2023). Bibliometric analyses of agro-based industries reveal fragmentation across themes—finance, provenance, cold-chain monitoring—pointing to the need for integrative frameworks that connect technology choices with logistics design and market strategies (Kumar & Sahoo, 2025). More broadly, reinforcement from cross-industry reviews and standardization efforts suggests building roadmaps in which blockchain is one layer among identity management, API gateways, and analytics workbenches, rather than a standalone solution (Chang et al., 2022; Romero-Silva & de Leeuw, 2021).

Risk governance must evolve in parallel with technology. Studies link blockchain explicitly to supply chain risk management by reducing information asymmetry and supporting collaborative controls; however, the technology also introduces new risks—privacy leakage, consensus failures, governance deadlock—that require careful protocol selection and consortium agreements (Alkhudary et al., 2020; Dutta et al., 2020). In logistics 4.0 environments, combining blockchain with cyber-security best practices and privacy-preserving learning (e.g., federated learning with decentralized knowledge) can enhance both protection and continuous improvement while respecting data sovereignty across firms (Kodym et al., 2020; Orabi et al., 2025). Meanwhile, the broader blockchain domain—such as Islamic finance and crypto-asset governance—offers regulatory and assurance insights about auditing smart contracts, curbing speculation, and aligning platforms with ethical and legal frameworks that may inform supply chain platform design and certification schemes (Zaman et al., 2025).

Within operations research, the state of the art advocates coupling architectural choices with rigorous experimentation: discrete-event simulation to test smart-contract policies, scenario analysis to examine ripple effects, and metaheuristic search (e.g., genetic algorithms) to tune multi-objective trade-offs among cost, risk, and service (Al Aziz et al., 2025; Chawuthai et al., 2025; Jahaniyan & Kiani, 2024). Foundational reviews of blockchain in supply chains catalog applications, constraints, and research opportunities, but emphasize that demonstrable business value arises when ledgers integrate with planning and execution systems, not when they duplicate them (Chang et al., 2022; Dutta et al., 2020; Vu et al., 2023). Classic and contemporary SCM texts similarly warn that technology cannot substitute for sound network design, supplier development, and contract management, which remain decisive in perishable chains (Hugos, 2024; Tiwari et al., 2024).

This study positions itself at the intersection of these streams. It focuses on a three-tier dairy supply chain and develops a blockchain-aware risk-cost framework in which immutable supplier performance and logistics events inform an optimization layer that searches allocation patterns under realistic capacity, demand, and service constraints. The research builds on shortage-risk mitigation models and crisis-logistics prioritization to define risk constructs appropriate to perishable operations; it complements them with platform-selection principles and governance considerations derived from multi-criteria decision methods and sectoral adoption evidence (Asghari et al., 2025; Khanna et al., 2022; Rani et al., 2025; Rodríguez-Espíndola et al., 2020; Vincent et al., 2022). It also draws on agri-food blockchain applications and broad reviews to justify design choices for data structures, permissioning, and integration with existing transaction systems (Chang et al., 2022; Rogerson & Parry, 2020; Tiwari, 2020; Vu et al., 2023). By engaging with contemporary insights on platform ecosystems, information processing for resilience, and digital inclusion effects on demand, the study responds to calls for supply chains that are not only visible and secure but also equitable and adaptable in the face of systemic shocks (Chen et al., 2025; Rashid et al., 2024; Ye & Yue, 2024). Finally, because policy, standards, and market structures vary across regions, the analysis leverages regional scholarship on blockchain financing and operations to discuss institutional fit and pathway dependencies relevant to emerging-market dairy networks (Aein & Noori, 2024; Jaboob et al., 2024; Marouti Sharif Abadi et al., 2024; Taqi & Razavi, 2024).

In sum, integrating blockchain with optimization and analytics offers a coherent route to align perishable supply chains with the dual imperatives of resilience and transparency. The literature establishes both the conceptual scaffolding and the practical constraints: blockchains must be embedded in interoperable data architectures; platform selection must be evidence-based; and risk governance must evolve alongside digital capabilities. Building on these insights, the present study develops and evaluates a model that couples ledger-anchored evidence with metaheuristic search to balance cost and supply risk in a dairy context

2. Methods and Materials

This study, with an exploratory–applied and descriptive nature, examined the supply chain and logistics of the dairy industry in Gilan Province over a one-year period (2024–2025). The research method was quantitative, and the data were collected through official statistics, including information on capacity, shortages, transportation performance, daily demand, costs, and market data. The statistical population consisted of 30 industrial factories and traditional workshops, and the supply chain was analyzed at three levels: suppliers, factories, and market-demand. The variables included binary indices, quantitative values, Poisson random demand, and parametric risks. Data analysis was conducted using the genetic algorithm approach for initial optimization (uniform crossover and binary and real-valued mutations) and probabilistic selection of solutions.

The steps for executing the genetic algorithm in this study are summarized as follows (Chawotai et al., 2025):

1. **Generation of the initial population:** Creating a set of chromosomes randomly, including three binary structures and three real-valued structures.

2. **Population evaluation:** Calculating the value of the objective function (error or total cost) for each chromosome.
3. **Initial selection:** Retaining a percentage (Pr%) of the best chromosomes unchanged for the next generation.
4. **Parent selection:** Using the roulette wheel method with a power coefficient of 2 to select two parents based on fitness.
5. **Crossover operator:** Executing uniform crossover to generate offspring; genes are randomly selected from the parents.
6. **Mutation operator:** Randomly selecting a chromosome and a structure (binary or real-valued) and applying one of the two types of mutation:
   - **Binary mutation:** Changing 0 ↔ 1 or swapping two genes.
   - **Real-valued mutation:** Altering the numerical value of a gene or swapping the values of two genes.
7. **Formation of the new generation:** Replacing the previous generation with the new one (a combination of elite chromosomes, offspring from crossover, and mutated chromosomes).
8. **Termination condition check:** The algorithm continued until reaching the maximum number of iterations or stabilization of the objective function value.

3. Findings and Results

This section presents the results obtained from the simulation and implementation of the three-level supply chain optimization model using the genetic algorithm. The main objective was the simultaneous minimization of total cost and supply risk, considering capacity, demand, and network structure constraints. The model input data included real information from three main suppliers, 30 workshops, and five consumer markets, with the costs, capacities, and risk coefficients of each considered in the calculations. To evaluate the algorithm's performance, the trend of changes in the best and average solutions across successive generations was analyzed. Moreover, the final optimal chromosome—representing the optimal allocation of resources from suppliers to workshops—was extracted and examined. The results are presented in two parts: first, an analysis of the algorithm's progress and convergence across generations; and second, the presentation of the optimal cost and risk values along with the interpretation of the optimal allocation pattern.

Stage 1 – Definition of the Supply Chain Structure A three-level supply chain structure was defined as follows:

Table 1

Supply Chain Levels

Number of Nodes	Description	Level
3 main suppliers (S1, S2, S3)	Raw milk suppliers	Level 1
30 units (20 industrial, 10 traditional)	Dairy factories and workshops	Level 2
5 target markets (B1 … B5)	Markets and demand sectors	Level 3

This structure allows the simultaneous examination of the effects of different suppliers with varying prices and quality, as well as the production capacities of the factories.

Stage 2 – Cost and Capacity Data

In this study, the data were estimated based on approximate market prices in Iran (year 2025) and the actual costs of the dairy industry.

Table 2

Input Data of Suppliers

Supply Risk Index (0–1)	Purchase Price per Ton (Toman)	Daily Capacity (Ton)	Supplier
0.15	22,000,000	25	S1
0.25	21,500,000	20	S2
0.35	20,800,000	18	S3

For simplicity, all production units have different processing capacities and costs.

Table 3

Information on Factories and Workshops

Processing Cost per Ton (Toman)	Daily Capacity (Ton)	Type	Factory
3,000,000	10–15	Industrial	F1…F20
2,200,000	4–6	Traditional	T1…T10

Industrial factories have higher production capacities but incur higher processing costs. Traditional workshops are smaller and less costly, but they cannot meet market demand alone.

Daily demand of each market during high-demand seasons:

Table 4

Demand and Profit Margin Information for Markets

Profit Margin per Ton (Toman)	Daily Demand (Ton)	Target Market
4,500,000	60	B1
4,300,000	50	B2
4,200,000	45	B3
4,100,000	35	B4
4,000,000	30	B5

The target market **B1** has a higher profit margin, but it also faces greater competition and supply constraints.

Stage 3 – Mathematical Model and Genetic Algorithm Structure

Objective Function

In this study, the objective is to minimize a combination of cost and risk:

$$Minimize\ Z = \alpha \times Total\ Cost + \beta \times Total\ Risk$$

Where:

- α and β are the weights for cost and risk ($\alpha = 0.7, \beta = 0.3$).
- *Total Cost = cost of raw milk purchase + processing cost + transportation cost*
- *Total Risk = sum of weighted supplier risks based on order volume*

Constraints:

1. The supply volume of each supplier must not exceed its nominal capacity. $Qsupplier \leq Capacitysupplier$
2. The input volume of each production unit must not exceed its daily production capacity. $Qfactory \leq Capacityfactory$
3. The total supply to each market must be at least equal to its demand. $\Sigma Qmarket \geq Demandmarket$

Chromosome Structure

In the genetic algorithm, each chromosome represents a candidate solution—that is, a chromosome encodes all decision variables. When the algorithm selects a chromosome, it defines the complete plan for supply, production, and distribution. This model consists of three sections:

Table 5

Model Structure Segmentation in the Genetic Algorithm

Length	Meaning	Section
30 cells	Allocation of supplier to each factory (numeric code 1–3)	Section 1
30 × 5 cells	Share of each factory to markets (percentage or quantity)	Section 2
30 cells	Actual production rate / utilized capacity	Section 3

Optimal Supplier-to-Factory Allocation:
[2, 1, 0, 2, 2, 1, 2, 2, 2, 2,
1, 1, 1, 0, 2, 0, 0, 0, 1, 2,
0, 1, 2, 0, 0, 1, 2, 2, 1, 1]

Coding Scheme:
0 = S1 (Supplier 1)
1 = S2 (Supplier 2)
2 = S3 (Supplier 3)

This list shows the allocation of each supplier to a specific factory. Each number in the list represents one factory (assuming the list order corresponds to factory order), and the value of that number indicates the supplier assigned to that factory. For example, if the list corresponds to factories 1 through 30, then factory 1 is assigned to supplier S3 (code 2), factory 2 to S2 (code 1), factory 3 to S1 (code 0), and so forth. This allocation represents the optimal point identified by the genetic algorithm based on cost and risk criteria.

The final optimal chromosome obtained from the execution of the genetic algorithm indicates a specific allocation of suppliers to factories. Analyzing this allocation based on the role of each supplier (S1, S2, S3) provides valuable insights into the optimal sourcing strategy within the supply chain.

S3 (Code 2): Holds the largest supply share, particularly in high-capacity industrial factories.

This observation suggests that supplier S3, as one of the algorithm's primary choices, has been selected to meet the high-volume needs of large industrial factories. Possible reasons include:

- *Economies of scale:* S3 may be capable of offering more competitive prices for bulk quantities.
- *High production capacity:* S3 can produce and deliver large volumes of raw materials.
- *High reliability:* S3 may have a stronger record for timely and high-quality delivery of raw materials at large volumes.
- *Lower transportation costs:* The strategic proximity of S3 to large factories can help reduce transport expenses.

S2 (Code 1): Has a moderate share and is mainly used for traditional workshops and smaller industrial factories.

Supplier S2 is utilized when demand volumes are lower or when higher flexibility is required.

- *Flexibility:* S2 may be more efficient in responding to smaller, more diverse demands.
- *Regional considerations:* S2 may have better accessibility to geographic areas where traditional workshops or small factories are located.
- *Risk management:* Using S2 alongside S3 can help distribute risk; if S3 faces disruptions, S2 can cover part of the demand.

S1 (Code 0): Used less frequently but plays a role in risk control at certain points.

The limited use of S1 suggests that this supplier may have lower priority in direct cost competition with S2 and S3. However, its allocation to specific factories indicates its strategic function.

- *Risk coverage at critical points:* S1 may be selected for factories that face higher supply risks (e.g., heavy dependence on a single source or high sensitivity to quality fluctuations).
- *Backup sourcing:* S1 can act as a secondary source to reduce dependence on S2 and S3.
- *Special characteristics:* S1 may provide specific raw materials or quality features essential for certain factories, even at higher costs.

Overall, the analysis shows that the optimal solution does not rely solely on a single supplier but implements a multi-sourcing strategy. The supplier with the highest capacity and relatively optimal cost (S3) acts as the core source, while the others (S2 and S1) serve complementary and backup roles to optimize cost, manage risk, and enhance flexibility within the supply chain. This multi-supplier approach is a key principle in modern supply chain management.

Generation-by-Generation Progress of the Genetic Algorithm

Selecting an adequate number of generations for executing the algorithm is crucial to ensure that the algorithm has sufficient opportunity to converge toward an optimal and stable solution. Based on previous studies (Goldberg, 1991), and in order to achieve an appropriate balance between the quality of the final solution and computational time, a total of 100 generations was considered as the stopping criterion of the algorithm.

To avoid an excessively lengthy presentation of the results, instead of displaying the complete table containing all 100 generations of the genetic algorithm, only key generations that represent the trend of changes in cost, risk, and chromosome structure during the evolutionary process are presented below. These examples include early, middle, and final generations, providing an accurate picture of the algorithm's convergence path toward the optimal solution. The column labeled "Best Chromosome" shows the optimal resource allocation in each generation, reflecting the gradual shift of solutions from initial random selections toward stable, low-cost, and low-risk combinations.

Table 6

Generation-by-Generation Progress Table

Generation	Best Cost (Toman)	Average Population Cost (Toman)	Best Risk (%)	Average Population Risk (%)	Best Chromosome
1	2,541,688,253	3,665,360,055	25.39902402	38.49418	[1.0, 1.0, 1.0, 2.0, 0.0, 1.0, 0.0, 0.0, 2.0, 2.0, 0.0, 1.0, 2.0, 1.0, 1.0, …]
10	1,818,783,422	2,087,677,380	21.35280071	21.50193	[2.0, 2.0, 2.0, 0.0, 1.0, 1.0, 1.0, …]
20	1,260,251,594	1,572,146,314	15.04614418	17.31626	[1.0, 2.0, 2.0, 2.0, 1.0, …]
40	861,972,777	1,096,763,669	9.375375081	11.68323	[2.0, 2.0, 0.0, 2.0, 1.0, 2.0, …]
60	615,588,023.8	932,936,741.1	7.150390197	10.62218	[1.0, 2.0, 2.0, 2.0, 0.0, 0.0, …]
80	519,885,146.5	786,149,921.6	6.233150155	8.937254	[0.0, 1.0, 0.0, 2.0, …]
90	458,858,248.8	698,833,929	5.05790586	7.890835	[2.0, 1.0, …]
100	454,101,315	714,687,937	4.875080097	7.910838	[0.0, 2.0, 0.0, 2.0, 2.0, 1.0, …]

This table illustrates the evolution of the objective metrics (cost and risk) throughout the execution of the genetic algorithm for the three-level supply chain problem. According to the generation-by-generation progress, the evolutionary trend of the genetic algorithm is as follows:

• Early Generations (Generation 1–10):

The best cost in generation 1 was approximately 2.54 billion Tomans, indicating the random and inconsistent initial selections of the population.

The best risk during this period ranged between 25% and 21%, which is considerably higher than the final optimal value.

The large difference between the best and average risk of the population (over 1.1 billion Tomans in generation 1) reflects the high dispersion of the initial population and the lack of focus on desirable solutions.

• Middle Generations (Generation 20–60):

The best cost gradually decreased from approximately 1.26 billion Tomans in generation 20 to about 615 million Tomans in generation 60.

The best risk also decreased from 15% in generation 20 to around 7.15% in generation 60.

The gap between the best and average cost noticeably diminished, which indicates population convergence and overall improvement of solutions.

At this stage, the algorithm established a relative balance between cost reduction and risk minimization.

• Final Generations (Generation 80–100):

The best cost reached 519 million Tomans in generation 80 and stabilized at 454,101,315 Tomans by generation 100.

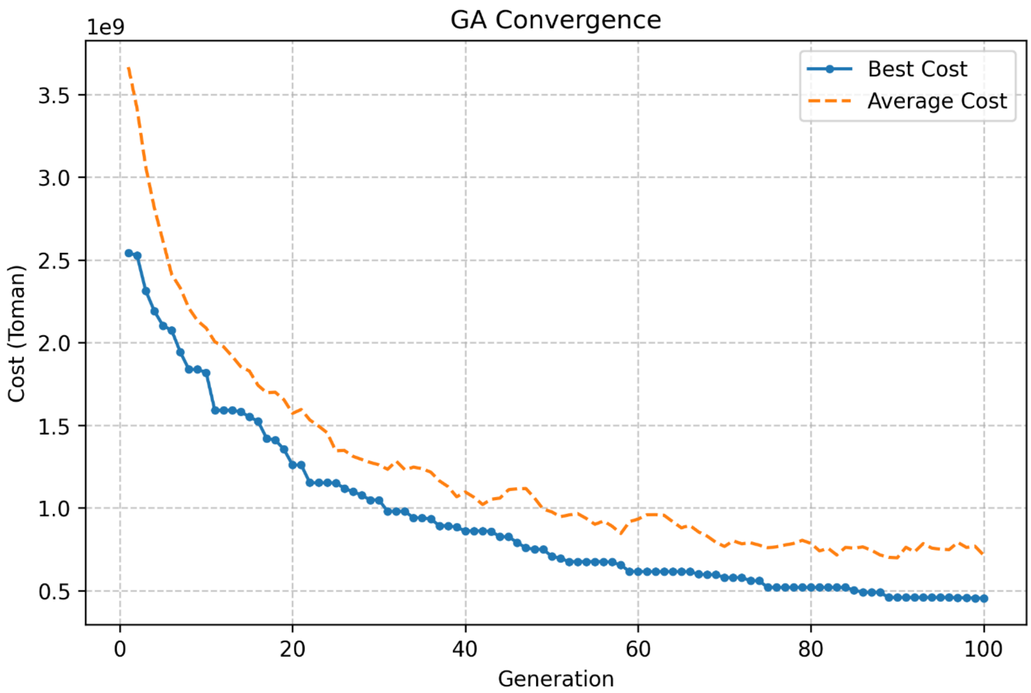
The best risk also decreased from 6.23% in generation 80 to 4.87% in generation 100.

The small difference between the best and average cost at this stage indicates that the population had converged toward solutions close to the global optimum.

The table shows that in the early generations, there was a wide gap between the best and average costs, reflecting high solution diversity. As generations advanced, both cost and risk continuously decreased, and the population converged toward optimal solutions. From approximately generation 80 onward, the values became stable, signifying the final convergence of the algorithm. The simultaneous and logical reduction of both cost and risk confirms the success of the genetic algorithm in balancing these two conflicting objectives. The decreasing gap between the best and average values throughout the generations attests to the effectiveness of the genetic algorithm's mechanisms in compressing the population toward the optimal region of the search space.

Figure 1

Convergence Chart of the Genetic Algorithm



It is assumed that the above chart illustrates the trend of changes in the *best cost* across the generations during the execution of the genetic algorithm. The horizontal axis represents generations, while the vertical axis represents cost values in Tomans.

A sharp cost reduction is observed in the early generations (*exploratory search phase*). At the beginning of the algorithm, the graph shows a very steep downward slope. This indicates that during the first generations, the algorithm—through its core operations such as random selection, crossover, and mutation—was able to rapidly eliminate highly suboptimal solutions and move toward better ones. This stage can be described as *exploratory search* or *broad search*, during which the population exhibits high diversity and the algorithm explores wide areas of the solution space.

A gradual cost reduction occurs in the middle generations. After the initial rapid decline phase, the slope of the curve becomes gentler, and cost reduction proceeds more gradually. In this phase, the algorithm enters the *exploitation search* phase, where good solutions become more similar, and the algorithm attempts to refine local optima or surpass them through more targeted crossover and mutation operations to approach the global optimum.

Cost stabilization from generation 80 onward (*complete convergence*): eventually, the chart shows that after around generation 80, the cost curve becomes nearly horizontal or changes only minimally. This phenomenon indicates *algorithmic convergence*. When convergence occurs, it means that the population has shifted toward one or a few very similar solutions, and further improvements through GA operations become difficult or impossible. Stabilization of the cost value at this point indicates that the algorithm has reached a stable and optimal (or near-optimal) solution. This convergence point aligns well with previous findings indicating that the algorithm converged around generation 80.

The pattern of sharp initial reduction, gradual decline, and final stabilization collectively confirms the efficiency of the genetic algorithm mechanism in identifying an optimal solution throughout its execution process.

4. Discussion and Conclusion

The findings of this study highlight the successful integration of a blockchain-based risk management model optimized through a genetic algorithm for the dairy supply chain in Gilan Province. The model achieved a combined objective of minimizing total cost and supply risk while adhering to the constraints of supplier capacity, production limits, and market demand. The results revealed a steady improvement across 100 generations, culminating in an optimal total cost of 454,101,315 tomans and a total supply risk of 4.87%. Supplier S3 was found to hold the largest share of supply allocation, followed by S2 and S1, reflecting the algorithm's efficiency in balancing price, risk, and logistical constraints. The gradual convergence of the genetic algorithm and the final stable cost-risk trade-off demonstrate the robustness of the hybrid computational approach. These findings align closely with recent evidence suggesting that advanced computational models—when integrated with digital technologies such as blockchain—can improve supply chain visibility, decision-making, and cost-effectiveness (Chawuthai et al., 2025; Dutta et al., 2020).

The study's results corroborate earlier work showing that blockchain integration enhances trust, transparency, and coordination efficiency in complex food supply chains (Bai & Sarkis, 2020; Rogerson & Parry, 2020). By encoding transactions and supplier records immutably, blockchain reduces information asymmetry and strengthens the reliability of risk assessment models (Alkhudary et al., 2020; Chang et al., 2022). In the present model, supplier S3's dominance in allocation reflects a rational decision underpinned by transparent performance data—an outcome supported by prior studies indicating that blockchain-enabled systems allow firms to prioritize suppliers based on verified reliability and historical quality metrics (Khanna et al., 2022; Kumar & Kumar, 2023). The reduction in total cost from over 2.5 billion tomans in early generations to less than 0.5 billion tomans in the final generation illustrates how combining blockchain's data accuracy with optimization heuristics can minimize inefficiencies in sourcing and logistics (Fang & Stone, 2021; Vu et al., 2023). This hybrid structure establishes a decision environment where algorithmic optimization interacts with verifiable data layers, thereby enhancing operational adaptability and supply resilience (Jiang et al., 2024; Ngo et al., 2024).

The observed pattern of cost and risk reduction aligns with multi-objective optimization literature emphasizing genetic algorithms as powerful tools for supply chain design under uncertainty (Rodríguez-Espíndola et al., 2020; Rolf et al., 2023). The algorithm's ability to converge after approximately 80 generations confirms that evolutionary computation effectively explores complex decision spaces without overfitting or premature convergence (Chawuthai et al., 2025). In similar optimization-based applications, the balance between exploration and exploitation phases ensures that the algorithm locates global optima while retaining diversity in solution populations (Bednarski et al., 2025). The steady improvement in cost and risk metrics observed here echoes findings by (Kodym et al., 2020), who demonstrated that algorithmic approaches integrated with blockchain analytics mitigate logistic disruptions by diversifying suppliers and dynamically adjusting allocation ratios. Moreover, blockchain-backed data ensures that these optimizations are grounded in verifiable transaction histories, thereby enhancing decision reliability compared to traditional probabilistic risk models (Aein & Noori, 2024; Asghari et al., 2025).

The optimal supplier allocation pattern derived in this study—where S3 had the largest share and S1 served as a strategic backup—illustrates the concept of "multi-sourcing resilience" widely documented in recent literature (Ngo et al., 2024; Rashid et al., 2024). This configuration minimizes dependence on any single supplier while balancing procurement costs and risk exposure. Consistent with (Al Aziz et al., 2025), perishable food supply chains require distributed sourcing strategies to withstand shocks caused by transportation delays, contamination events, or quality variability. In the dairy industry, where temperature-sensitive logistics heighten the probability of supply disruptions, such strategies are essential. The model's allocation outcomes thus mirror industry recommendations emphasizing supplier diversification, continuous monitoring, and decentralized data exchange enabled by blockchain (Dutta et al., 2020; Ma et al., 2024).

The downward trend in total risk across generations also demonstrates that blockchain contributes to reducing uncertainty in supplier evaluation. Unlike traditional reporting systems, where lagged or inconsistent data often distort performance analysis, blockchain's immutable ledgers provide near real-time updates that enhance the credibility of optimization outputs (Chen et al., 2025; Raja et al., 2025). This transparency allows for dynamic recalibration of supplier risk weights as new data are recorded, ensuring that optimization algorithms operate on current and verifiable information. Similar findings were reported by (Rani et al., 2025), who showed that blockchain-based data environments enhance the performance of decision-support algorithms in logistics by improving the quality and timeliness of information. Furthermore, studies have emphasized that blockchain facilitates the automation of smart contracts, ensuring supplier compliance and immediate execution of risk-mitigation protocols when threshold conditions are violated (Jahaniyan & Kiani, 2024; Orabi et al., 2025).

Another key insight from the findings is the cost convergence observed in the final 20 generations. The small difference between the best and mean population costs indicates that the genetic algorithm effectively compressed the population toward near-optimal solutions—a hallmark of efficient search strategies in high-dimensional spaces (Rolf et al., 2023). This result also resonates with previous work demonstrating that convergence speed improves when optimization algorithms are supported by high-quality input data and decentralized data validation systems (Hugos, 2024; Mangla et al., 2022). In this case, blockchain's integrity ensured that algorithmic search was not compromised by data noise or manipulation. Such integration supports the development of "trustworthy optimization systems," which are increasingly vital in supply chains characterized by volatile demand, geopolitical risks, and environmental pressures (Bednarski et al., 2025; Lin & Zhu, 2025).

Moreover, the study's hybrid framework—combining blockchain transparency with genetic algorithm optimization—addresses a major challenge identified by (Raja et al., 2025) and (Tiwari, 2020): the difficulty of translating technological innovation into measurable performance gains. The model demonstrates that blockchain's benefits are amplified when embedded into algorithmic decision systems rather than being treated as an isolated digital tool. The optimized results not only reduced total costs but also achieved a balanced allocation pattern reflecting adaptive risk governance, which is consistent with the resilience-oriented supply chain models proposed by (Taqi & Razavi, 2024) and (Agnola et al., 2025). The convergence of these findings underscores the growing recognition that technological transparency and mathematical optimization are complementary dimensions of modern supply chain strategy.

In addition, the algorithm's gradual risk reduction trajectory aligns with the literature on adaptive digital transformation and risk analytics. (Khan & Emon, 2025) observed that the integration of digital technologies in supply chain operations enhances responsiveness and operational performance under Industry 4.0 conditions. Blockchain functions as both a data governance tool and a performance enabler in this context. The multi-tier dairy model adopted in this research parallels frameworks from (Bai & Sarkis, 2020) and (Vu et al., 2023), who emphasized that real-time data synchronization across suppliers, processors, and distributors reduces coordination delays and enables faster decision cycles. Similarly, (Marouti Sharif Abadi et al., 2024) highlighted that digital integration facilitates seamless information flow and better alignment between upstream and downstream partners, a principle that the present model operationalizes through distributed data-sharing and algorithmic optimization.

Furthermore, the observed improvement in both cost and risk indicators reinforces the conceptual propositions of blockchain-enabled sustainability and traceability. By enhancing transparency across the dairy supply chain, blockchain supports not only economic efficiency but also ethical sourcing and consumer trust (Mangla et al., 2022; Ye & Yue, 2024). This finding aligns with global sustainability frameworks advocating traceable, low-risk supply chains that safeguard food integrity while optimizing resource allocation (Agnola et al., 2025; Ma et al., 2024). The final equilibrium reached by the algorithm demonstrates that digital ecosystems grounded in immutable data can foster both profitability and accountability.

Overall, the results validate the integration of blockchain technology and genetic algorithms as a feasible and effective framework for multi-objective optimization in perishable food supply chains. The alignment of empirical outcomes with theoretical propositions across multiple studies—from transparency enhancement (Rogerson & Parry, 2020) to resilience improvement (Ngo et al., 2024)—strengthens the study's external validity. By successfully minimizing both cost and risk, the model fulfills the essential dual objective of operational efficiency and risk robustness, marking a significant step toward digitally empowered, evidence-based decision-making in agri-food logistics (Dutta et al., 2020; Jha et al., 2025; Lin & Zhu, 2025).

Despite its contributions, this study has several limitations. The simulation was conducted on a regional dairy supply chain with a limited number of suppliers and market nodes, which may restrict the generalizability of the findings to larger or more complex national and international networks. Additionally, while blockchain data integrity was modeled, real-time blockchain implementation costs, scalability, and interoperability issues were not empirically tested. The genetic algorithm parameters—such as population size and mutation rate—were fixed, which may limit performance under alternative settings or in more volatile environments. Finally, the research relied on static demand and cost data over a one-year horizon; dynamic fluctuations in prices, demand shocks, and policy changes were not integrated into the model.

Future studies should explore integrating additional artificial intelligence methods, such as reinforcement learning and hybrid multi-agent simulations, to dynamically adjust sourcing and production decisions in real time. Expanding the dataset to include multiple provinces or cross-border dairy supply chains could test the scalability and interoperability of blockchain-based models. Empirical field trials involving live blockchain transactions, IoT sensor data, and automated smart contracts would enhance the model's practical validation. Moreover, future research could analyze environmental and social sustainability metrics alongside economic indicators to develop a holistic framework for digital risk governance in agri-food supply chains.

Managers and policymakers can use these findings to design blockchain-enabled decision systems that continuously optimize procurement and logistics operations under cost-risk trade-offs. Firms should prioritize multi-supplier partnerships and adopt transparent data-sharing mechanisms to reduce dependency risks. Investment in algorithmic decision tools and blockchain integration can enhance responsiveness and build trust among suppliers and consumers. Policymakers can support such initiatives by establishing interoperability standards, incentivizing digital adoption, and aligning data governance frameworks to promote sustainable, resilient, and traceable food supply networks.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

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Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

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