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# Analyzing Competitive Strategies in Factoryless Manufacturing Using Agent-Based Simulation

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## ABSTRACT

**Objective**: This study addresses the fabless manufacturing business model's increasing relevance and complexity of decision-making. The primary aim is to develop and evaluate a simulation model for analyzing competitive strategies and optimizing managerial decisions in fabless supply chains.

**Methodology:** An agent-based simulation approach was employed to model interactions between fabless companies and manufacturing factories. The decision-making process for manufacturing partners was based on three key criteria: quality, cost, and availability. The simulation was implemented using AnyLogic software and analyzed under competitive and non-competitive market scenarios. Validation was conducted using real-world data to ensure model accuracy and applicability.

**Results**: The study reveals that the weighting of criteria—quality, cost, and availability—significantly affects company performance in fabless manufacturing supply chains. Companies prioritizing quality tend to gain long-term advantages, while those focusing on cost may achieve short-term profits but struggle with sustainability. Competition complicates the balance of these criteria, leading to increased system-wide costs. These findings emphasize the need for nuanced strategies in dynamic markets.

**Conclusion**: The developed simulation model offers a robust quantitative framework for analyzing and optimizing decision-making in fabless manufacturing supply chains. It is a valuable decision-support tool for managers, enabling them to adopt optimal strategies that reduce costs, enhance product quality, and improve customer satisfaction in dynamic and competitive market conditions.

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## Introduction

The twenty-first-century economy has fundamentally transformed the nature of business operations. Once centered on tangible assets such as factories and machinery, the traditional corporate valuation model has been replaced by a new paradigm in which intangible assets, including design, innovation, brand equity, and supply chain management, play a dominant role (Shkodina et al., 2020). In this new paradigm, companies have moved away from direct ownership of production and adopted more flexible, network-based structures *(Fuchs et al., 2021).* Driven by globalization and the digital revolution, these transformations have created new business models such as factoryless manufacturing.

In recent decades, manufacturing firms have evolved in response to changing customer demands and increasing market competition (Ayazi et al., 2023; ElMaraghy et al., 2021). Initially, companies conducted all production processes within their own facilities (Fuchs et al., 2021). However, with globalization and access to lower-cost labor, outsourcing emerged as a key strategic approach (Grimaldi et al., 2022), enabling firms to concentrate on their core competitive advantages.

Factoryless manufacturing represents a more advanced stage of outsourcing, in which the entire production process is delegated to external manufacturing partners. Examples such as Apple and Nike demonstrate how companies that focus on design, engineering, and marketing can reduce fixed costs, manage demand uncertainty, and gain access to specialized expertise (Pessot et al., 2021; Samad et al., 2023). This business model enhances agility, enabling firms to respond quickly to market changes and transform innovation into market-ready products.

Nevertheless, decision-making in selecting appropriate manufacturing partners poses significant managerial challenges. These strategic choices must balance conflicting criteria such as cost, quality, and availability (Samad et al., 2023). Poor partner selection may lead to quality deterioration, brand damage, and strategic failure in a dynamic competitive environment. Therefore, analytical tools are essential to support these critical decisions.

Modeling and simulation of manufacturing processes enable virtual experimentation aimed at improving system performance (Ageyeva et al., 2019; Jabarie et al., 2025). Such tools provide valuable insights for decision-making regarding production structure, logistics, and scheduling adjustments (Lewicki et al., 2024). Even modified system configurations can be simulated to enhance operational efficiency further.

Despite the growing number of factoryless manufacturing firms, notable research gaps remain. Existing studies are largely static in nature and often overlook the competitive interactions among companies (Kabus et al., 2022; Kim et al., 2024). This research gap underscores the need for dynamic simulation models to explore competition and partner selection mechanisms within the factoryless manufacturing paradigm.

Accordingly, this paper aims to address two fundamental research questions:

1. How can agent-based simulation be used to model the complex dynamics of factoryless manufacturing?
2. How can competition among factoryless manufacturers shape partner selection and collaboration in a specific industry, and how can this be effectively modeled?

The answers to these questions can substantially contribute to theoretical and practical knowledge in factoryless manufacturing, providing actionable insights for improving the performance of such businesses. The main contribution of this research lies in developing an agent-based simulation framework capable of analyzing various competitive strategies under dynamic market conditions and quantitatively evaluating the trade-offs among key criteria such as cost, quality, and availability.

The modern concept of manufacturing has emerged through a long evolutionary process rooted in the economic and technological transformations of the twentieth century (Yin et al., 2018). During the mid-twentieth century, advancements in transportation systems and trade liberalization allowed leading nations to dominate global production by leveraging comparative advantage and economies of scale (Bayard et al., 2013; Gómez-Reino et al., 2023). However, since the late twentieth century, a “great divergence” has occurred, in which production processes have been decomposed into discrete tasks distributed across the globe(Coyle & Nguyen, 2022). This phenomenon laid the groundwork for the emergence of global value chains and new business models in which physical production became separated from design and marketing activities (Loonam & O’Regan, 2022).

Amid these transformations, factoryless manufacturing emerged as the ultimate manifestation of this separation (Hur & Yoon, 2022). Originating in the U.S. apparel industry during the 1950s (Coyle & Nguyen, 2022), this strategy is built upon the complete separation of two core functions: (1) design, engineering, and marketing, and (2) physical production(Pessot et al., 2021). Factoryless firms fully outsource the manufacturing process to a network of production partners, while concentrating their internal capabilities on high–value-added intangible activities (Bergeaud et al., 2024). As evidenced by the success of firms in the semiconductor sector, this approach aims to reduce fixed costs, enhance flexibility, and access specialized external resources (Bayard et al., 2013).

Numerous studies have identified the strategic advantages of factoryless manufacturing, including lower initial investments, higher flexibility in responding to market fluctuations, access to advanced technologies, and a stronger focus on core competencies (Samad et al., 2023). This model also enables faster market entry and reduces operational risks.

Despite these advantages, factoryless manufacturing presents substantial managerial challenges, particularly in managing a complex, dynamic, and uncertain system (Coyle & Nguyen, 2022). Selecting appropriate manufacturing partners requires the simultaneous assessment of conflicting criteria such as cost, quality, and availability (Masoudi & Shahin, 2022). These decisions are not made in isolation but within a dynamic competitive environment where the actions of one firm influence others. Managing this level of complexity and mitigating associated strategic risks requires powerful analytical tools. In this context, simulation has proven to be an effective method for modeling and analyzing complex manufacturing and business systems (Firouzabadi et al., 2018; Lucas et al., 2015). Simulation allows managers to experiment with alternative scenarios without disturbing the real system, identify bottlenecks, and forecast the outcomes of different strategic options (Lewicki et al., 2024).

While traditional simulation approaches (such as discrete-event simulation) often adopt a top-down perspective, agent-based simulation (ABS) provides a unique bottom-up approach to analyzing complex phenomena (Alizadeh Asari et al., 2025; Macal, 2016). In ABS, a system is represented as a collection of autonomous and interactive “agents,” each characterized by attributes, behaviors, and decision-making rules (Ayazi et al., 2025a). These agents interact with one another and their environment, generating emergent system-level behaviors (Klügl & Bazzan, 2012). Previous studies have highlighted the potential of ABS for modeling complex supply chains, risk management, and interactions among economic actors (Iannino et al., 2020; Younespour Candidate et al., 2023).

Key features of agent-based simulation—such as adaptive agent behavior that allows dynamic strategy adjustment, heterogeneity that enables modeling agents with diverse characteristics (e.g., manufacturers with different quality or cost levels), and decentralized interactions where global patterns emerge from local decisions—make it a powerful tool for studying complex systems. These characteristics closely align with the nature of factoryless manufacturing (Ayazi et al., 2025b; Macal, 2016).

A literature review reveals that most studies in this field have focused on descriptive or macro-level analyses. Early research primarily examined the general benefits and challenges of the factoryless model (Pooryanasab et al., 2023; Xing, 2021). More recently, scholars have moved toward quantitative and analytical approaches. Studies by Coyle & Nguyen (2022) and Hur & Yoon (2022) explored the economic implications of this model, showing that factoryless manufacturing can significantly reshape industry structures and trade patterns.

Despite this growing body of research, several critical gaps remain:

- Lack of quantitative modeling: Most existing studies are descriptive and do not offer comprehensive quantitative frameworks for analyzing factoryless systems.
- Neglect of competitive dynamics: Current research focuses on individual firms, overlooking competitive interactions among factoryless manufacturers.
- Limited modeling of decision-making processes: The complex decision logic underlying partner selection has not been comprehensively captured.

The literature review thus indicates that factoryless manufacturing represents a rapidly growing business model characterized by complex decision-making challenges in a competitive environment. Given its bottom-up nature and ability to represent autonomous decision-making agents, agent-based simulation provides a highly suitable methodological approach for studying these challenges.

However, a clear research gap remains: despite the strong theoretical fit of ABS, its practical application in modeling competitive strategies among factoryless manufacturers—particularly in the context of partner selection—has been largely unexplored (Kabus et al., 2022; Kim et al., 2024). Although the literature on factoryless manufacturing and partner selection is expanding, most reviews and empirical studies have focused on descriptive analyses of advantages and disadvantages, with limited critical examination of decision-making processes or identification of knowledge gaps. Existing models are often either conceptually strong but lack methodological linkage to real-world institutional contexts, or empirically grounded but structurally simplistic.

To address these limitations, this study develops an agent-based model that contributes to the literature in two ways:

1. It introduces a simulation framework that explicitly models competitive interactions among factoryless firms, emphasizing the trade-offs in partner selection criteria.
2. It incorporates practical and institutional considerations to connect better model-based insights with real-world managerial decision-making and industrial constraints.

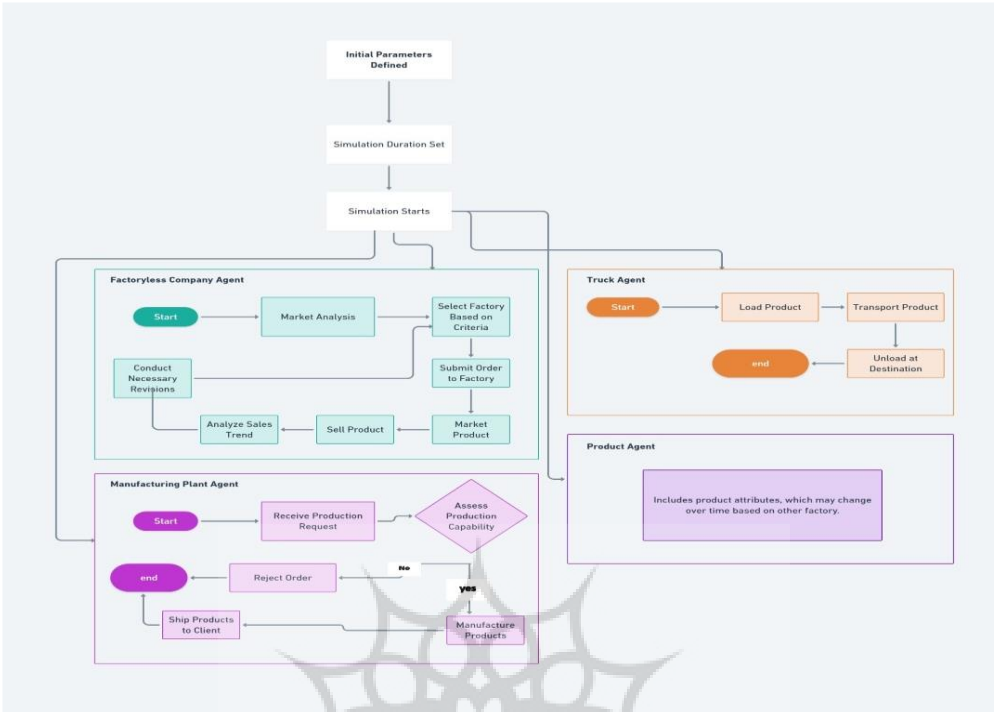


**Figure 1. Architecture of the Agent-Based Simulation Model and the Flow of Interactions among Agents**

## Materials and Methods

This study employs an agent-based modeling (ABM) approach to simulate the decision-making behavior of factoryless manufacturing firms within a supply chain context. Additionally, scenario analysis is applied to examine the influence of key factors on policymakers' strategic decisions. This combined approach enables policymakers and managers to anticipate alternative economic and environmental conditions and to select appropriate strategies under uncertainty.

### Factoryless Manufacturing Framework

In the factoryless manufacturing business model, the production process is fully outsourced, while the firm focuses its internal resources on product design, marketing, and sales activities.

Figure X illustrates the key stages of this process, which include:

- Identifying market needs,
- Designing the product,
- Placing manufacturing orders with selected production partners,
- Conducting market analysis, and
- Marketing and selling the final products.

The factoryless manufacturer leverages its design and marketing expertise in this model while utilizing partner factories' production capacity. This structure minimizes production costs, enhances flexibility, and enables faster responses to dynamic market changes.

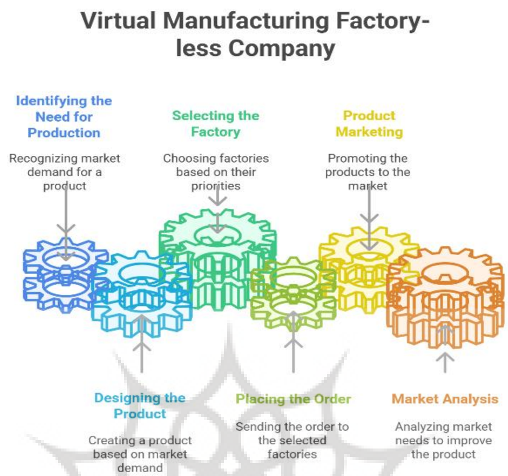


**Figure 2. Product Manufacturing Structure in a Factory-less Company**

The figure schematically illustrates the various stages of a factoryless manufacturing company's operations. This process begins with identifying market needs and designing a corresponding product. Subsequently, the company places production orders with selected contract manufacturers. After production, the products are delivered to the company, and the market analysis and product marketing process commences. In this model, the factoryless company plays a key role in supply chain management and product marketing, while other factories perform the actual manufacturing. This structure allows the company to focus on its core competencies and benefit from the advantages of outsourcing.

In the factoryless manufacturing process, following product design and market analysis, one of the most critical and sensitive stages is selecting a suitable manufacturing partner. This choice requires a thorough evaluation of available options based on key criteria.

**Simulation Structure**

In this simulation, there are four main types of agents: the Company Agent, representing a factoryless manufacturing company; the Factory Agent, representing a manufacturing plant; the Product Agent, representing a product; and the Truck Agent, responsible for the transportation of products. Each agent plays a specific role and has a distinct objective within the simulation. Figure 1 illustrates the structure of the agent-based simulation.

The simulation process begins by receiving initial data and setting the start time. The Company Agent performs key tasks, including product design, manufacturer selection, order placement, marketing, and analyzing market feedback. The Factory Agent assesses its production capacity and, after manufacturing, delivers the products to the Truck Agent. The Truck Agent is responsible for transporting and delivering the product to its destination. Furthermore, as a dynamic variable, the Product Agent manages the product's attributes and influences the interactions between other agents. This structure comprehensively models the supply chain interactions. In the table below, each of the parameters presented in the paper is described in detail:

**Table 1. Abbreviations and Descriptions**

| Parameters | Description |
|---|---|
| $f(score_{factory})$ | Factory Score Evaluation Function: This value represents the final score of a factory, calculated based on a combination of cost, quality, and availability. Based on this score, the factoryless company selects from the available manufacturing partners. |
| $x_{t_{factory}}$ | Represents the total production output of a factory at a specific time t. |
| $rejected_{t_{factory}}$ | Represents the quantity of defective products from a factory at time t. These products are rejected for failing to meet quality standards. |
| $w_{cost}$ | A coefficient representing the importance of cost in the overall factory evaluation. This value is set between 0 and 1. |
| $f(cost_{factory})$ | Factory Cost: The costs associated with product manufacturing at a factory, including raw materials, labor, and other expenses. This cost varies for each factory.. |
| $w_{Quality}$ | Quality Weight: A coefficient representing the importance of the quality of manufactured products in the overall evaluation. This value is also set between 0 and 1. |
| $Quality_{factory}$ | Factory Quality: The quality level of the products manufactured at a factory is determined by its quality standards. This metric is based on the average quality of previously manufactured products. |
| $w_{availability}$ | Availability Weight: A coefficient representing the importance of the factory's availability (such as production capacity or delivery time). This value is also set between 0 and 1. |
| $f(availability_{factory})$ | Factory Availability: The factory can deliver products on time and meet customer demands. |
| $order_{factory}$ | The number of orders remaining in the production queue at a manufacturing factory, awaiting production |
| $f(rejected)_{ratio}$ | This parameter defines the proportion of non-defective (good) products to the total products manufactured by a factory. The value of this parameter ranges from 0 to 1. |
| $resource_{capacity}$ | Production Line Ratio: The ratio of a factory's number of production lines to the maximum number available across all factories. This parameter ranges from 0 to 1. |
| $f(quality_{ratio})$ | This represents the normalized production quality of a factory. The value of this parameter ranges from 0 to 1. |
| $quality\_level_{factory}$ | This indicates the quality level of products manufactured by a factory, which can take values on a scale from 1 to 5. |
| $max\_quality\_level$ | Maximum Quality Value: Represents a product's highest possible quality rating, which is set to 5 in this model. |

In the decision-making process of the factoryless manufacturing company, the evaluation and selection of a manufacturing partner are based on three key indices: cost, quality, and availability (Coyle & Nguyen, 2022; Masoudi & Shahin, 2022; Raynal-Ljutovac et al., 2005). To this end, a comprehensive scoring system has been designed to calculate each index quantitatively. This scoring system is executed dynamically and continuously throughout the simulation, updating calculations at each decision-making stage.

In the first step, the manufacturing quality ratio of the factory is calculated. This ratio is obtained by dividing the quality level of the factory under consideration by the highest available quality level among all factories. This index indicates how closely the evaluated factory aligns with the desired quality standards. This calculation outputs a value between zero and one, where a value closer to one signifies higher quality. Equation 1 shows the manufacturing quality ratio.

$$f(quality_{ratio}) = \frac{quality\_level_{factory}}{max\_quality\_level} \tag{1}$$

The ratio of non-defective products from previous purchases is analyzed in the second step. This index is calculated by the ratio of the difference between the total products manufactured and the rejected products, to the total number of manufactured products. This metric evaluates the factory's historical performance in producing quality goods and indicates the percentage of past production that has met quality standards. The formula for the ratio of non-defective products from previous purchases (Fulfilled Demand Ratio) is calculated as follows in Equation 1.

$$f(rejected)_{ratio} = \frac{\sum_1^t x_{t_{factory}} - \sum_1^t rejected_{t_{factory}}}{\sum_1^t x_{t_{factory}}} \tag{2}$$

The cost of manufacturing products at each factory is calculated in the third step. This index is derived from a composite of three influential factors: the quality ratio, the factory's resource capacity, and the yield rate (Ding, 2011; Polishchuk & Bernadska, 2020). This calculation allows for comparing manufacturing costs by incorporating quality and operational factors. The formula for calculating the manufacturing cost per factory is presented in Equation 3.

$$\boldsymbol{f(cost_{factory})} = f(quality_{ratio}) + resource_{capacity} + f(rejected)_{ratio} \tag{3}$$

In the fourth step, the manufacturer's availability is determined using a uniform distribution, factoring in the factory's existing order backlog. A uniform distribution is chosen as a logical assumption for the initial modeling phase due to the lack of pre-existing information on specific availability patterns. This measure serves as a baseline indicator of the factory's capacity to take on new orders and its capability to execute them. The calculation for factory availability is presented in Equation 4.

$$f\left(availability_{\boldsymbol{factory}}\right) = uniform(0, \frac{1}{order_{factory}}) \tag{4}$$

Finally, the overall score for each factory is calculated through a weighted combination of the three key indices: availability, cost, and quality (Coyle & Nguyen, 2022; Masoudi & Shahin, 2022; Raynal-Ljutovac et al., 2005). This calculation assigns a weight to each cost, quality, and availability criterion, corresponding to its importance within the factoryless manufacturing company's strategy. The sum of these weights equals one, and the final score provides a comprehensive metric for comparing and selecting the optimal manufacturing partner. Equation 5 shows the formula for each factory's score, which the factoryless company agent utilizes for decision-making.

$$f\left(score_{factory}\right) = (w_{cost} * f(cost_{factory})) + (w_{Quality} * Quality_{factory}) + (w_{availability} * f\left(availability_{\boldsymbol{factory}}\right)) \tag{5}$$

This multi-criteria scoring system, implemented within the simulation environment, is executed continuously at each stage of the decision-making process. In effect, these formulas constitute a core part of the decision-making logic for the intelligent agents. In each time step, the calculations are re-executed based on new conditions and updated information. This dynamism in the calculations enables adaptive decision-making and an appropriate response to environmental changes, allowing the factoryless company to make precise and rational decisions for manufacturer selection by simultaneously considering all critical aspects.

It should also be noted that post-sale products are evaluated using a customer satisfaction index. A product is deemed satisfactory if it meets the end-user's quality expectations. This outcome, in turn, significantly impacts the company's future sales.

For the initial validation of the model, operational data from the "Alpha Company"—including key factory performance parameters such as quality, unit cost, and production capacity—were used as inputs for the simulation.

**Institutional Constraints and Conditions of the Iranian Industry**

To enhance the model's practical applicability for local studies, it is essential to explicitly incorporate the unique constraints and characteristics of the Iranian business environment into the analysis. These constraints include the instability of tariff and import policies, customs complexities and time-consuming clearance procedures, financing constraints for small and medium-sized enterprises (SMEs), weaknesses in highly scalable supply networks, and limitations in the skilled workforce. Furthermore, the structure of contracts and legal relationships between the buyer and the factory in Iran may introduce legal and operational risks that differ from those in other regions. Incorporating these characteristics into the model's parameters (e.g., by introducing an increased probability of availability delays, a distribution for unpredictable costs, or constraints on allocated capacity) would enable the testing of adaptive policies and scenario planning for managerial decisions under the country's real-world conditions.

## Results

This section presents the results of the agent-based simulation conducted using AnyLogic software. The analysis comprises two main parts: non-competitive scenarios to examine the system's baseline behavior, and competitive scenarios to study the impact of strategic interactions among the companies.

### Non-Competitive Scenarios

In the non-competitive setting, the performance of a factoryless manufacturing company, "Alpha," was analyzed in interaction with multiple manufacturing plants. To evaluate performance, four primary scenarios were designed with a focus on the criteria of quality, cost, availability, and a balanced approach among these metrics. Each scenario was replicated 10 times to ensure the validity of the results. It was assumed in these scenarios that two factories would be capable of manufacturing the products for the factoryless company.

**Table 2. Results of Non-Competitive Scenarios**

| Row | Strategy | Average Total Cost (System Cost Unit) | Factory Share (%) | | Percentage of Defective Products | Customer Satisfaction (%) | Percentage of Market Demand Fulfillment |
|---|---|---|---|---|---|---|---|
| | | | Factory 1 | Factory 2 | | | |
| 1 | Criteria Balance | 4.27 | 59 | 41 | 10 | 50 | 65 |
| 2 | Cost Priority | 2.52 | 51 | 49 | 6 | 60 | 61 |
| 3 | Accessibility Priority | 3.82 | 56 | 44 | 4 | 49 | 80 |
| 4 | Quality Priority | 4.79 | 59 | 41 | 2 | 50 | 90 |

The table above illustrates the performance of the factoryless manufacturing system under non-competitive conditions, where a single factoryless manufacturing company interacts with and utilizes several manufacturing plants for production. The results are also presented as a bar chart in Figure 3 to understand these outcomes better.

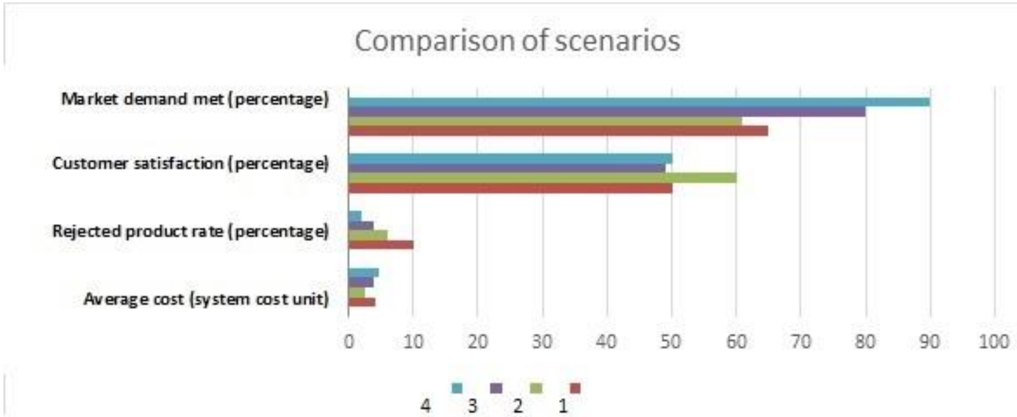


**Figure 3. Bar Chart Comparing the Simulation Results in the Non-Competitive Scenario**

The results indicated a moderate and balanced performance in the first scenario, where a balanced strategy was implemented by assigning equal weight to all criteria. The average cost was 4.27, and customer satisfaction stood at 50%. This benchmark scenario demonstrates that a general strategy without a specific focus leads to average, non-optimized outcomes. This balance is logical, as the model, without a clear priority, naturally gravitates towards options with comparable scores across the three criteria, thereby avoiding extreme choices (e.g., very cheap and low-quality, or costly and high-quality).

In the second scenario, by assigning a high weight to the cost criterion, the model, as expected, automatically selected factories with the lowest manufacturing costs. This strategy successfully reduced the average final cost from 4.27 to 2.52 units, a significant accomplishment. However, this cost reduction was achieved at the expense of quality and responsiveness. As shown in Table 2, the fulfilled demand rate decreased from 65% to 61%. This outcome illustrates a classic trade-off in management: cheaper factories likely used lower-quality raw materials or had more limited production capacity, leading to reduced satisfaction and an inability to meet demand fully. This scenario clearly shows that a sole focus on cost, while financially attractive, can harm other key performance indicators and damage the company's reputation in the long run.

When the strategy was focused on maximizing availability, the model significantly increased the fulfilled demand rate to 80%, the highest rate of responsiveness among the scenarios that controlled for cost. This improvement stems from the model selecting factories with higher order-acceptance capacity and faster delivery times. However, this choice was not without consequences; customer satisfaction dropped to its lowest level (49%). This suggests that factories capable of faster production may have less stringent quality control. This scenario is relevant for companies operating in markets that demand rapid response but also carry the inherent risk of diminished quality.

In this scenario, with a complete focus on quality, the results in operational indices were impressive. The rate of rejected products was minimized (2%), and the fulfilled demand rate reached 90%, indicating the high reliability of the selected factories. This superior performance is attributed to the model's selection of factories with the highest standards and the best quality track records. However, this qualitative excellence pushed the final cost to its highest level (4.79 units). This scenario confirms that achieving premium quality requires substantial investment and is a necessary, albeit costly, strategy for companies that build their brand on quality.

## Competitive Scenarios

In this section, the analysis of competitive scenarios focused on four leading actors: two factoryless manufacturing companies and two factories capable of producing the products. The simulations for each scenario were replicated ten times to ensure the accuracy and reliability of the results.

The particular significance of this study lies in its examination of competitive conditions between factoryless manufacturers, as this competition can create instability within the companies' collaborative network. This instability can, in turn, have a considerable impact on the relationships among the network's actors and the overall performance of the supply chain.

**Table 3. Results of Competitive Scenarios**

| Row | Strategy | Average Total Cost (in System Cost Units) | | Comparison of Product Rejection Rates between the Two Competitors | Customer Satisfaction (%) | Market Demand Fulfillment Ratio between the Two Competitors |
|---|---|---|---|---|---|---|
| | | Case Study | Competitor | | | |
| 1 | Criteria Balance | 3.31 | 3.62 | Equal | 49 | Equal |
| 2 | Cost Priority | 3.03 | 3.93 | Decrease in Demand for the Case Study Company | 43 | Decrease in Responsiveness Capability |
| 3 | Accessibility Priority | 3.32 | 4.56 | Equal | 40 | The demand was completely fulfilled |
| 4 | Quality Priority | 4 | 5 | Increase in Demand for the Case Study Company | 70 | The demand was completely fulfilled |

This table illustrates the performance of two factoryless manufacturing companies operating in a competitive environment with two available production factories.

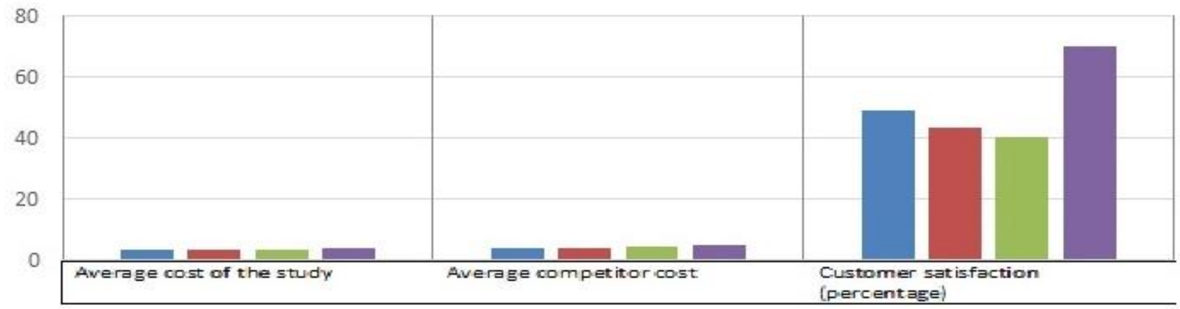


**Figure 4. Simulation Results in the Competitive Scenario**

Competition fundamentally alters the nature of decision-making, necessitating the selection of the best option and an analysis of competitors' choices. The results indicate that competition increases overall system costs; for instance, in the quality-focused scenario, costs rose under competitive conditions due to the scarcity of high-quality resources.

Both companies adopted a balanced strategy in the first scenario, resulting in a perfect market equilibrium. Average costs, customer satisfaction, and market share were divided equally (50%/50%). This scenario demonstrates that competition devolves into a zero-sum game without a differentiating strategy, requiring companies to adopt distinct strategic paths to gain an advantage.

In the second scenario, the company under study, by focusing on cost reduction, significantly lowered its production costs (3.03 vs. 3.93), but its market share fell to 42%. The selection of cheaper factories led to lower quality and customer satisfaction (65% vs. 70%). This outcome suggests that a cost leadership strategy is only successful if quality is a lower priority for customers.

In the third scenario, focusing on rapid availability increased the company's market share (55%), but production costs surged (4.56 vs. 3.32). This strategy is effective for rapid market penetration but is not financially sustainable and requires cost optimization for long-term success.

In the fourth scenario, the focus on quality resulted in higher customer satisfaction (92% vs. 72%) and a dominant market share (65%), although production costs reached their peak (5.0 vs. 4.0). These results indicate that quality, in this simulated market, is a robust and sustainable competitive advantage that reinforces customer loyalty. Investing in quality control and selecting superior manufacturing partners is an effective strategy for building a long-term competitive edge.

The results show that companies assigning greater weight to quality achieve more sustainable competitive advantages in the long run; this finding aligns with studies that emphasize the importance of quality and manufacturing capabilities (Damirchi et al., 2025). Conversely, an explicit focus on cost reduction may yield short-term profitability but increases the long-term risks of market share erosion and declining customer loyalty. Furthermore, competition among companies led to increased total system costs, corresponding with theoretical concepts illustrating the complexities of supply networks. These findings suggest policymakers and managers should adopt hybrid and phased strategies rather than pursuing one-dimensional policies.

## Validation

The model was validated through the following three stages: (1) micro-face validation, (2) macro-face validation, and (3) input validation (Fraccascia et al., 2021).

1. Micro-face validation criteria are met because the model's mechanisms and features are defined in a manner consistent with the existing literature. For instance, the indices such as quality and cost, which influence decision-making in the factoryless manufacturing process, were extracted from the literature, ensuring they correspond to real-world mechanisms.
2. Macro-face validation criteria are satisfied as the model's dynamics are consistently defined with the literature. For example, companies decide to establish a relationship with a factory only if the potential economic benefits are higher than those offered by competing manufacturers, implying that an optimal choice is made. This aligns with real-world dynamics.
3. Each scenario was replicated 10 times using identical inputs for input validation. These replications demonstrated that the results consistently followed the same pattern. This strong consistency and reproducibility in the outputs clearly indicate high numerical stability and the correctness of the simulation code's implementation, showing that the internal model is robust and reliable.

## Conclusion

This research aimed to model and analyze factoryless manufacturing processes and to answer two primary questions: how to model the complex process of factoryless manufacturing using an agent-based simulation approach, and how competition between factoryless companies shapes their selection of and collaboration with manufacturing partners.

In response to the first question, the results demonstrated that agent-based simulation with AnyLogic software can effectively model the complex interactions among various agents and facilitate the analysis of parameters such as cost, quality, and availability in strategic decision-making. The model also evaluates the impact of strategic decisions and competitive dynamics in the market, illustrating the interdependent effects of companies' decisions on one another.

Regarding the second question, the results from the competitive scenarios revealed that competition among companies influences their factory selection strategies and overall performance. A balanced performance across different indices was observed in the first scenario (equal weighting). In the second scenario (cost focus), production costs decreased (3.03 and 3.93 for the two companies), but customer satisfaction declined. Demand responsiveness increased in the third scenario (availability priority), but costs rose (3.32 and 4.56). In the fourth scenario (quality focus), customer satisfaction and the rate of non-defective products increased, but costs reached 4.0 and 5.0 units, respectively.

Competition leads companies to focus on one or two specific criteria, while simultaneously increasing overall system costs and making it more challenging to achieve a balance among metrics. Although competition can improve product quality, it also leads to higher costs and variability in demand responsiveness and customer satisfaction. These findings underscore the importance of analyzing the weighting of criteria and competitive strategies to enhance performance and optimize decision-making.

Practical Recommendations from this research are provided in four main areas to improve the performance of factoryless manufacturing companies:

- Decision-Making Strategies: Companies should adopt a balanced approach to weighting decision criteria (short-term) and develop dynamic systems for evaluating factory performance (medium-term). Additionally, optimizing the factory selection process in response to changing market conditions can enhance efficiency (long-term).
- Supply Chain Management: It is recommended that long-term relationships with key factories be established, integrated information management systems be developed, and real-time performance monitoring systems (long-term) be implemented. These actions will help increase supply chain transparency and efficiency.
- Quality Management: Developing integrated quality standards and advanced quality control systems is essential (short-term). Employee training and improving inspection and control processes can guarantee product quality and increase customer satisfaction (medium-term).

- Cost Management: Optimizing production processes and developing accurate costing systems are highly important (long-term). Efficient inventory management and reducing transportation costs can also help lower overall system costs and enhance the company's competitiveness (short-term).

## Research Limitations

This study faced two main categories of limitations:

1. Data Limitations: Insufficient access to real-world data and transparency for specific parameters.

2. Generalizability Limitations: Regional and cultural differences, the rapidly changing business environment, and the diversity of business models make it difficult to generalize the findings to all industries.

## Directions for Future Research

The findings of this research suggest three primary areas for future investigation:

- Enhancement of Simulation Models: Incorporating more complex parameters and advanced algorithms to better understand system dynamics and market complexities.
- Comparative Studies: Comparing the performance of factoryless manufacturing companies across different industries with traditional companies, and analyzing regional differences and success factors.
- Strategic Research: Studying pricing strategies, the role of innovation and technology, and investigating new business models and market entry strategies.



## Data Availability Statement

The data supporting this study's findings are available from the corresponding author upon reasonable request. Due to privacy or ethical restrictions, the data are not publicly available.

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## Ethical considerations

This article contains no studies involving human participants or animals performed by the authors.

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## Conflict of interest

The authors declare no conflict of interest.

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