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Financial Performance and Beer Distribution Game with Competition: Comparison of Supply Chains Without Strategy, Simple Moving Average and Single Exponential Smoothing

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Abstract

Background: Supply chain management is challenged by demand uncertainty, inventory inefficiency, and rising operational costs. Existing Beer Distribution Game (BDG) studies generally overlook competitive dynamics and consumer trust considerations.
Objective: This study compares the financial performance of BDG scenarios using no forecasting, SMA, and EMA strategies under competitive conditions and evaluates their impact on consumer shifts.
Methods: A quantitative simulation-based experimental approach was employed using a modified Beer Distribution Game model developed in AnyLogic. The model incorporated consumer trust dynamics and competition mechanisms. Three forecasting scenarios were tested through 5,000 simulation replications. Financial performance was measured using total operational costs across retailer, wholesaler, distributor, and factory units. Data were analyzed using one-way ANOVA, followed by Bonferroni and Games-Howell post-hoc tests at a significance level of 0.05.
Results: The results revealed significant differences among the three forecasting scenarios. The Single ES (EMA) strategy achieved the lowest average total operational cost (USD 1,163.07), significantly outperforming SMA (USD 1,771.21) and the no-strategy scenario (USD 1,810.81). EMA consistently reduced costs across all supply chain units, including retailer, wholesaler, distributor, and factory levels. However, EMA also generated the highest average consumer shift rate (32.90%), indicating a trade-off between cost efficiency and customer retention. The findings further suggest that adaptive forecasting improves supply chain stability and partially mitigates the bullwhip effect under competitive conditions.
Conclusion: EMA offers superior cost efficiency, but should be complemented by customer retention strategies to ensure sustainable performance.

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INTRODUCTION

The global market is shifting from traditional industries to the service sector, driven by developments in information technology. This enables real-time integration of marketing, accounting, and inventory data, and encourages the emergence of internet-based e-commerce, electronic data interchange, and the use of barcodes. These changes have created new competition that demands speed, accuracy, and precision in decision-making, requiring companies to allocate additional resources to ensure the reliability of information. In this context, the global market cannot be separated from the supply chain as a long network of production and distribution entities, where uncertainty in demand, inventory problems, and limitations in information sharing are difficult to avoid Bloomfield (2013) and Wei (2019) and have the potential to incur excessive costs if not managed systematically.

One model that is widely used to analyze these dynamics is the Beer Distribution Game (BDG) (Macdonald et al., 2013; Roser et al., 2020). BDG was introduced by Jay Forrester in the 1960s as a simulation of a dynamic supply chain system consisting of four main units, namely Retailer, Wholesaler, Distributor, and Factory. This model represents non-linear business processes and requires each unit to understand operations as a single system (Zhang et al., 2021). In the literature, BDG is used as a learning tool for the bullwhip effect, a means of testing variants or new concepts Sato (2020), and a medium for evaluating decision-making strategies to obtain the lowest total cost.

The BDG framework is based on a systemic thinking paradigm that views systems as interconnected units (Senge & Sterman, 1992). Disruptions in one unit can spread throughout the system and have a direct impact on total supply chain costs (Nguyen, 2020). With this approach, cost management is no longer the responsibility of a specific unit, but rather the result of collective interaction between all units. The application of systemic thinking in simulations and serious games has also been shown to support financing-based decision-making Saqib (2019) and Đula (2020), including in the context of cost management in the construction sector (Insja & Sihombing, 2017).

In addition to the systemic perspective, supply chain research distinguishes between deterministic and stochastic approaches. The deterministic approach risks producing large errors when uncertainty increases (Rushton et al., 2026). In contrast, the stochastic approach accommodates market nonlinearity and variability through random elements, thereby better reflecting consumer behavior and real market conditions (Wagner & Taudes, 1987). The advantages of the stochastic approach are evident in cost-benefit analysis and the selection of more adaptive decision alternatives (Khodabakhshi & Ahmadi, 2021).

BDG simulation is rooted in decision-making theory Macdonald (2013) and inventory theory (Alfieri & Zotteri, 2016). In conditions of uncertainty, each unit is expected to make rational decisions to minimize costs and maximize profits. Total costs in BDG generally consist of inventory costs and backorder costs, while other financial aspects such as investment and capital structure are not considered. Therefore, inventory management strategies are a key factor in determining the financial performance and Beer Distribution Game with Competition: Comparison of Supply Chains Without Strategy, Simple Moving Average and Single Exponential Smoothing.

Previous studies have shown that cost management strategies in BDG are greatly influenced by assumptions and the availability of information. The use of Q and ROP parameters has been reported to reduce total costs under certain conditions Alabdulkarim (2020) and Alfieri (2017), although their application is limited by data availability and the dominance of human decision-making. Other studies show that rational strategies do not always produce optimal performance Edali (2016), while information sharing has been shown to improve supply chain performance and reduce costs (Schnetzler & Schönsleben, 2007). Conversely, a lack of coordination and collaboration exacerbates the bullwhip effect and increases total costs (Roser et al., 2020; Baisa et al., 2024).

Stochastic forecasting-based approaches are gaining attention as solutions to BDG problems (Syntetos et al., 2016). Commonly used methods include Simple Moving Average (SMA), Single Exponential Smoothing (Single ES) also known as Exponential Moving Average (EMA), and ARIMA, as well as alternative approaches such as genetic algorithms (Strozzi et al., 2007). SMA and Single ES are widely used due to their simplicity and suitability for human decision-making behavior in BDG (Sterman, 2000; Merkuryeva et al., 2019; Ravinder, 2013; Nathania et al., 2021). However, most previous studies have focused on a single strategy or ignored competition and consumer trust.

The research gap is thus defined by the absence of comparative studies integrating stochastic forecasting methods with competitive supply chain behavior. The objective of this study is to identify the forecasting strategy that achieves the lowest total operational cost across all supply chain units in a competitive BDG setting. Theoretically, this study extends BDG literature by incorporating behavioral demand response through consumer trust decay as a competition mechanism, contributing a novel hybrid simulation framework. Practically, findings provide actionable guidance for supply chain managers in selecting forecasting methods under competitive pressure. The novelty of this research lies in the integration of consumer confidence dynamics into the BDG structure, enabling a more realistic representation of competitive market conditions than prior deterministic or single-strategy BDG models (Ali et al., 2017; Romagnoli et al., 2022). Despite extensive BDG research, a clear gap remains: most studies focus on a single forecasting strategy and neglect competitive dynamics and consumer trust as influencing factors. This study addresses this gap by simultaneously comparing three BDG scenarios, without forecasting strategy, with SMA, and with Single ES (EMA), in a competitive environment simulated via consumer confidence levels.

METHOD

This research is quantitative in nature and uses a simulation-based experimental method. This simulation or modeling is often classified as an exploratory or proof-of-concept model (Jobin et al., 2020).

Modeling is defined as a set of assumptions expressed in logical and mathematical relationships to understand processes in the real world (Law, 2015). Financial performance is an analysis applied to assess the extent to which a company has implemented rules in financial management appropriately and in accordance with applicable regulations. In this study, financial performance is determined based on total costs, with BDG having the best financial performance due to the lowest total costs. The definition of BDG according to Sterman (2000) is a role-based supply chain simulation designed by Jay Forrester in 1956, combining the concepts of system dynamics, simulation, and management. Meanwhile, competition is a situation where two parties (individuals/groups) compete to obtain something that cannot be shared (Enn, 2015).

The research instrument used was an experiment in the form of a simulation, which is a variant of BDG, and was developed with the help of AnyLogic software. The rules applied were mostly similar to the original version of BDG, as follows:

a. The four units involved in BDG have an initial stock of 25 in each warehouse. The process flow starts from consumer orders, then goes to the Retailer, Wholesaler, Distributor, and ends at the Factory. The Factory does not place orders to replenish its stock but replaces it with a production process.
b. BDG uses two inputs from users, *Threshold* and *Order*. The selection of the same Threshold and Order pair is intended to isolate the effect of forecasting strategies on total costs by reducing the complexity of ordering policy variations between units, so that observed differences in financial performance can be directly attributed to the forecasting method used, rather than to differences in inventory control parameters. Threshold describes the allowable stock limit. If this Threshold value is exceeded, each unit will start the ordering process. The amount of stock ordered is set in the Order input. In this case, the Order at the Retailer is the number of stock orders received by the Wholesaler, while the Order by the Wholesaler is the stock order going to the Distributor. In the three scenarios that being tested, the Threshold and Order values are set to have the same value.
c. BDG can be run at different times, and in this study, 1 cycle is set for 50 days (Roser et al., 2020). In each cycle, each unit has the same Threshold and Order (T/O) values, referring to the pull strategy (Roser et al., 2020; Tajima et al., 2023). The same T/O strategy, according to Oroojlooyjadid (2021), is the opposite of human players' strategies, which tend to be irrational, do not follow specific rules, and reflect situations where one unit can see the T/O choices of other units or where information sharing occurs. Lead time is set in a triangular distribution with values ranging from ½ to 1 ½ days, where the use of a triangular distribution refers to (Fairchild et al., 2016).

d. Consumer demand is regulated based on a uniform distribution, with values ranging from 0 to 20 per day. The uniform distribution was chosen to represent highly uncertain and irregular demand conditions, so that each demand value within the specified range has the same probability, allowing for testing the resilience of forecasting strategies in the face of high market variability. This level of consumer demand is based on Liu (2009), which discusses BDG optimization strategies using genetic algorithms and particle swarm optimization (PSO). The article states that with uniform distribution-based demand, total costs tend to increase and strategies are needed to suppress them. This level of consumer demand differs from the initial version of BDG, where consumer demand tends to be constant and only changes at the beginning of the game (Sterman, 2000).

e. Inventory costs are set at $0.50 per item remaining in the warehouse, while backlog costs are valued at $1 per item. If inventory costs are calculated based on excess stock, then backlog costs are calculated based on the stock shortage experienced by each unit. The factory determines the amount of stock to be produced (based on the order value) and can send it to distributors, wholesalers, and retailers if the stock in each unit is still insufficient. This condition is based on the Thompson (2015) system understanding strategy, which depends on decision-making and information availability. The main role is carried out by the Factory with the ability of the unit to control the amount of stock in the supply chain system. The role of the Factory is similar to the "closed communication loop" principle used by the garment giant Zara (Ferdows et al., 2004). Meanwhile, the ability to anticipate consumer orders is carried out by the Retailer through predictions using SMA and Single ES. The ability to anticipate consumer orders is an implementation of the concept of damped oscillation and stability in BDG (Lu, 2021).

The development model of BDG that incorporates consumer confidence levels and competition is structured as follows: 1) The initial level of consumer confidence is 1, and this value is set as the maximum value. 2) When a stockout occurs at the retailer, the reduction in consumer confidence ranges from 0.21 to 0.43 and is regulated in a uniform distribution (Corsten & Gruen, 2004). 3) Consumers with zero or negative trust levels will not place orders. 4) There is a store loyalty parameter that gives a 60% chance for consumers who already have a confidence level of zero or minus to return to shop at the retailer (Nagare & Dutta, 2014). Consumers who have returned are assumed to have an initial confidence level of 0.2. 5) When consumer orders can be fulfilled by retailers, consumer trust levels will increase by 0.2. Trust levels will continue to increase but will not exceed the maximum trust level of 1. The concept of consumer trust levels was born from the development of consumer behavior, namely inequity aversion and reciprocity, which are discussed in (Đula & Größler, 2020). The consumer confidence level is constructed using the discrete event facility in AnyLogic.

The analysis steps are as follows:

Statistical Hypothesis

H_0: There is no difference in the average financial performance between the three BDG modeling scenarios

H_1: There is at least one group with a significantly different average financial performance.

Experimental Design

The three BDG modeling scenarios were tested through BDG simulation and the financial performance results (total costs, costs at the retailer, costs at the wholesaler, costs at the distributor, factory costs) were recorded from each condition.

One-Way ANOVA Test

ANOVA tests were performed on the dependent variable of financial performance with the independent variable of BDG modeling with 3 scenarios (no forecasting strategy, SMA, and single ES). F-statistic and p-value values were used to determine statistical significance.

Post-hoc Test

If the ANOVA results show significance, a post-hoc test using Bonferroni or Games-Howell is performed to specifically identify which groups are significantly different.

Statistical Significance

The significance threshold is set at α = 0.05. Data analysis based on the table will also illustrate consumer shifts that occur due to competition. From the data generated by the experiment, it is possible that a strategy can result in minimal total costs, but the distribution of these total costs is not proportional. In other words, one unit may have much higher costs than the other units. Another possibility that arises is the high percentage of consumer shifts due to competition and its impact on total costs in a supply chain.

Data Validity Test

After developing the model using AnyLogic, this study continued with the model verification stage. Verification was carried out so that the conceptually developed model could be accurately represented in AnyLogic (Banks et al., 2005). Verification steps include debugging, third-party checks, and output and parameter checks to ensure that the output values generated are reasonable and consistent with the operational design logic of the system. The verification procedure is carried out by checking the logic flow between blocks, ensuring there are no deadlocks or entity flow errors, evaluating the consistency of time units and costs, and observing the behavior of the model under extreme conditions, such as zero requests or maximum requests, to ensure that the system response remains rational. In this study, the stage used is verification rather than validation because there is no data in the real-world system that can be used as a comparison.

The Source block is named Pesanan_Konsumen, which generates consumer orders based on uniform distribution. This order data is stored in Collection and used as historical data in the forecasting process using SMA and Single ES. In addition, the Kompetitor and Cek_Kepercayaan blocks are used to represent competitive conditions in the supply chain in this model. Competition is assumed to be the existence of alternative suppliers or distribution channels that can affect consumer confidence levels, where a decline in service levels due to stock shortages will reduce confidence and indirectly affect the demand received by retailers.

This assumption reflects competitive market conditions, where consumers have choices and respond dynamically to service levels. Competition is not modeled as direct interactions between companies, but rather as external pressures on consumer demand and trust, so that the focus of the analysis remains on the cost implications and internal decision-making within the BDG. All blocks used in this study are listed in Figure 1.

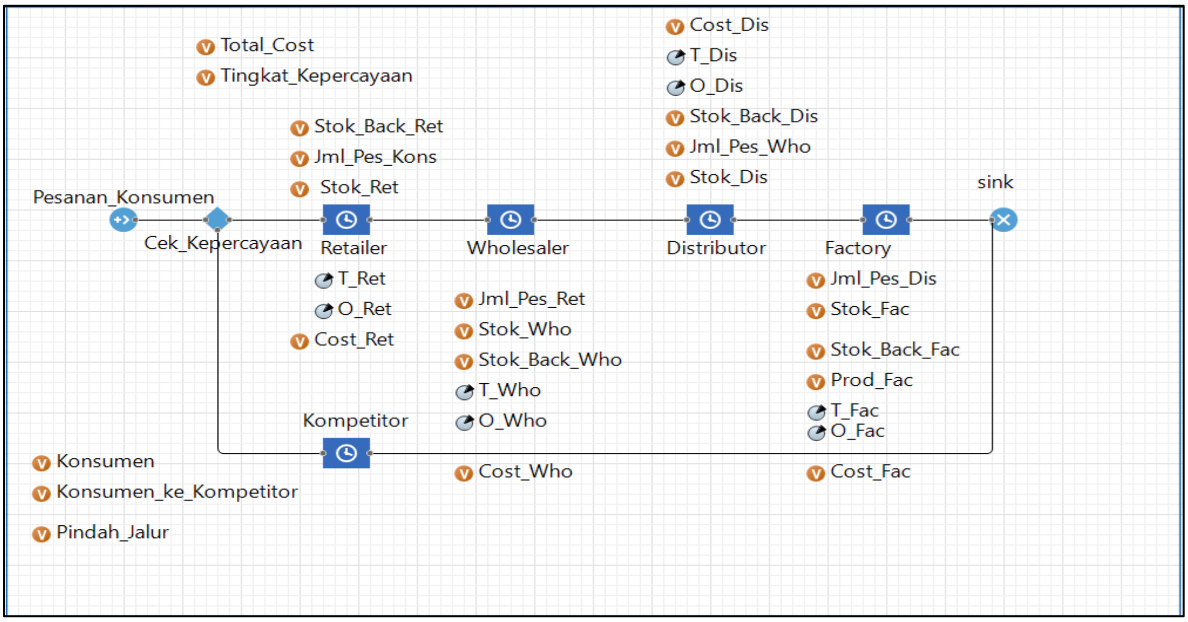
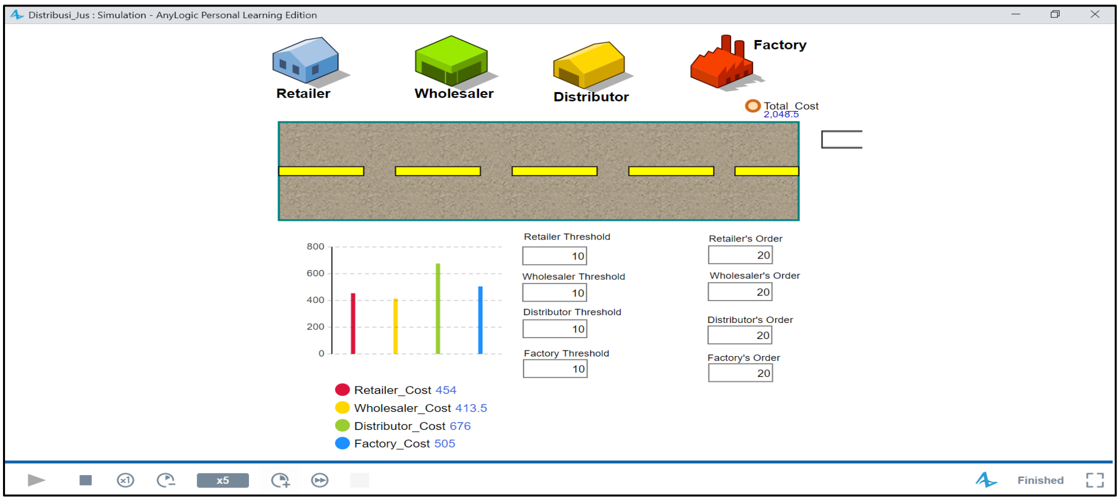


Figure 1 . Supply Chain with Competition in AnyLogic

RESULTS AND DISCUSSION

Results

The experiment began by applying the simulation framework according to Figure 1. After passing the verification step, the simulation was run for a period of one cycle (50 days), as shown in Figure 2 for a T/O value of 10/20.



Total_Cost 2,048.5

Retailer Threshold 10
Wholesaler Threshold 10
Distributor Threshold 10
Factory Threshold 10

Retailer's Order 20
Wholesaler's Order 20
Distributor's Order 20
Factory's Order 20

Retailer_Cost 454
Wholesaler_Cost 413.5
Distributor_Cost 676
Factory_Cost 505

Figure 2. Simulation results for one cycle at a T/O of 10/20

The simulation was then run with 5,000 replications/iterations, and the experimental results after replication on the Total Cost data are summarized in Table 1. Of the three scenarios tested, group 1 represents the scenario without a strategy, group 2 represents the SMA strategy, and group 3 represents the Single ES (EMA) strategy. Next, normality, homogeneity, ANOVA, and Games-Howell post-hoc tests were conducted on the total cost averages, with the results presented in Table 2.

The Kolmogorov-Smirnov significance values for the three groups were greater than 0.05, indicating that all three groups were normally distributed. A homogeneity test and ANOVA were then conducted, yielding a significance of variances value less than 0.05, which indicates that the data were not homogeneous. The ANOVA test also showed a significance value below 0.05, suggesting that differences exist between the three data groups. Following the homogeneity test, the Games-Howell post-hoc test was performed. The post-hoc test results, based on the mean difference values in the bottom row, show that the average of group 3 is 647.74 lower than group 1 and 608.14 lower than group 2. The significance value is below 0.05, indicating a statistically significant difference between the three average costs.

Table 1. Average total cost data

T/O	**Total Cost w/o Strategy**			**Total Cost w/ SMA**			**Total Cost w/ EMA**		
	Min	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**
1/5	863.00	1809.39	2,916.00	971.00	1,766.71	2,900.00	458.50	1166.29	2070.00
1/10	835.00	1807.88	3023.50	930.00	1,775.35	2,883.50	460.50	1,163.75	1,963.00
1/15	876.00	1815.59	3,365.50	874.00	1768.94	3046.50	488.00	1159.54	1,974.50
1/20	925.50	1807.94	2,987.00	866.00	1771.47	2852.50	405.00	1158.91	2099.50
5/5	912.00	1814.38	3033.00	875.00	1,767.30	2,921.00	404.50	1,166.63	2,265.50
5/10	846.00	1818.80	3014.50	924.00	1,768.77	2,970.00	347.50	1,163.03	2167.00
5/15	949.50	1807.97	2,959.90	892.00	1768.02	2,745.50	468.50	1163.16	2068.00
5/20	819.50	1808.34	3014.50	790.00	1,776.54	2,778.50	385.00	1163.03	2133.00
10/5	830.00	1816.99	2,830.50	901.50	1,775.70	2,969.50	472.50	1165.47	2,207.50
10/10	891.00	1809.70	2,982.50	956.00	1,772.71	2,961.50	503.50	1161.00	2126.50
10/15	929.50	1809.94	3,271.50	917.50	1774.88	2,949.50	367.00	1162.02	2133.50
10/20	860.00	1802.79	2784.00	843.50	1768.12	2737.50	394.50	1163.97	2043.50

Table 2. Testing on Total Cost

		Kolmogorov Smirnov Sig.	Variances	ANOVA	Games-Howell Sig.	(I) Group	(J) Group	Mean Difference (I-J)
Mean_TC	1	0.053	0.044	0.000	0.000	1	2	39.60000*
							3	647.74250*
	2	0.074			0.00	2	1	-39.60000*
							3	608.14250*
	3	0.2			0.000	3	1	-647.74250*
							2	-608.14250*

The next comparison is with retailer cost data, as summarized in Table 3. Testing was subsequently carried out on retailer data, with the results shown in Table 4. Based on the test results, retailer cost data are normally distributed because the Kolmogorov-Smirnov significance values of the three groups are greater than 0.05. From the homogeneity test, the variance significance value is less than 0.05, indicating that the data are not homogeneous. The ANOVA test yields a significance value of less than 0.05, indicating that there are differences between the three data groups.

Table 3. Average Retailer Cost Data

T/O	Retailer Cost w/o Strategy			Retailer Cost w/ SMA			Retailer Cost w/ EMA		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1/5	197.00	471.72	889.50	172.50	389.25	794.50	68.00	184.42	475.50
1/10	178.50	470.81	929.00	157.50	390.71	756.50	59.00	184.94	404.00
1/15	205.50	474.59	1034.00	147.00	390.31	739.00	63.00	183.68	454.50
1/20	193.00	471.92	882.00	143.00	390.49	763.50	62.50	183.59	428.50
5/5	160.00	472.90	926.50	172.50	389.87	717.00	61.50	184.46	468.00
5/10	165.50	474.90	882.50	162.00	390.59	828.00	65.00	184.23	468.00
5/15	228.00	471.30	832.50	161.50	390.52	711.50	63.00	183.90	446.00
5/20	188.50	471.96	970.00	144.50	391.22	737.00	65.50	184.48	429.00
10/5	196.00	473.40	875.00	148.50	392.10	793.50	48.00	183.70	446.00
10/10	188.00	472.25	862.50	183.50	390.73	777.50	61.50	183.20	438.50
10/15	196.00	471.91	926.00	167.00	390.36	787.00	61.00	184.34	419.50
10/20	179.50	470.71	887.00	161.50	390.48	751.50	49.00	184.27	451.00

Based on the results of the homogeneity test, the next procedure is the Games-Howell Post-Hoc Test. The Mean Difference value in the last row of the Post-Hoc analysis shows that the average of group 3 is 288.26 lower than that of group 1 and 206.45 lower than that of group 2. The Games-Howell Post-Hoc Significance value is below 0.05, indicating that there is a significant difference in retailer costs among the three scenarios.

Table 4. Testing on Retailer Costs

		Kolmogorov Smirnov Sig.	Variances	ANOVA	Games-Howell Sig.	(I) Group	(J) Group	Mean Difference (I-J)
Mean_Ret	1	0.195	0.011	0.000	0.000	1	2	81.81167*

							3	288.26333*
	2	0.076			0.000	2	1	-81.81167*
							3	206.45167*
	3	0.2			0.000	3	1	-288.26333*
							2	-206.45167

The next comparison was made on wholesaler cost data, as summarized in Table 5. Subsequent tests included normality, homogeneity, ANOVA, and Post-Hoc Bonferroni on the average wholesaler cost, with the results shown in Table 6. Based on the normality test, it was concluded that the wholesaler cost data were normally distributed because the Kolmogorov-Smirnov significance values for the three groups were greater than 0.05. Next, a homogeneity test was conducted, yielding a variance significance value greater than 0.05, indicating that the data were homogeneous.

Table 5. Wholesaler Cost Average Data

T/O	**Wholesaler Cost w/o Strategy**			**Wholesaler Cost w/ SMA**			**Wholesaler Cost w/ EMA**		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1/5	198.00	427.86	729.50	188.50	394.30	703.50	101.00	301.31	602.50
1/10	171.00	427.96	792.50	173.50	397.00	748.50	89.00	299.37	580.00
1/15	192.00	428.22	778.00	179.50	395.19	715.00	81.00	297.72	605.00
1/20	201.50	426.22	730.00	174.00	396.23	678.50	83.50	297.59	567.50
5/5	210.50	428.71	748.00	173.50	395.27	674.00	82.50	300.73	642.50
5/10	207.50	429.12	762.50	188.50	395.38	739.50	84.00	298.46	652.50
5/15	206.50	426.56	760.00	170.50	395.36	717.00	85.00	299.05	615.00
5/20	191.00	426.75	772.00	168.50	397.29	669.00	87.50	299.70	630.00
10/5	178.00	428.98	732.50	205.00	397.10	688.00	85.00	300.46	617.50
10/10	202.50	426.29	731.50	191.00	395.81	700.00	96.00	299.27	630.00
10/15	177.00	427.99	767.50	178.50	396.80	707.50	91.50	299.10	627.50
10/20	190.00	425.12	722.50	161.50	394.58	647.00	96.00	299.47	602.50

Table 6. Testing on Wholesaler Costs

		Kolmogorov Smirnov Sig.	**Variances**	**ANOVA**	**Bonferroni Sig.**	**(I) Group**	**(J) Group**	**Mean Difference (I-J)**
Mean_Who	1	0.195	0.527	0.000	0.000	1	2	31.62250*
							3	128.12917*
	2	0.2			0.000	2	1	-31.62250*
							3	96.50667*
	3	0.2			0.000	3	1	-128.12917*
							2	-96.50667*

The ANOVA test results show a significance value of less than 0.05, indicating that there are differences among the three data groups. Based on the homogeneity test results, the next step is the Bonferroni Post-Hoc Test. The Post-Hoc test results indicate a significance value of less than 0.05, suggesting significant differences among the three wholesaler cost averages across the tested scenarios. According to the Mean Difference value in the bottom row, the average for group 3 is 128.12 lower than that of group 1 and 96.5 lower than that of group 2. The next comparison was conducted using the distributor cost data, as listed in Table 7, with the corresponding test results presented in Table 8.

Table 7. Distributor Cost Average Data

T/O	**Distributor Cost w/o Strategy**			**Distributor Cost w/ SMA**			**Distributor Cost w/ EMA**		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1/5	210.00	461.03	782.50	242.50	501.13	912.00	135.00	345.56	645.00
1/10	194.50	460.20	777.00	217.50	504.13	887.50	122.50	345.14	652.50

1/15	224.00	462.55	788.50	232.50	501.60	920.00	142.50	344.60	628.50
1/20	211.00	460.93	848.50	242.50	502.21	891.00	120.00	343.71	678.50
5/5	212.50	462.32	841.00	255.00	501.70	849.50	95.00	345.86	744.50
5/10	245.00	463.69	786.50	221.00	501.42	906.50	101.00	345.29	674.00
5/15	202.50	461.47	783.00	254.50	501.32	897.00	130.00	345.00	660.00
5/20	222.50	460.53	835.00	250.00	503.94	889.00	112.50	344.21	640.50
10/5	223.00	462.97	813.00	245.00	503.05	834.00	125.00	345.52	697.00
10/10	237.50	461.50	857.50	254.00	503.38	875.50	131.50	344.28	643.00
10/15	215.50	460.97	865.00	252.50	505.25	865.00	102.50	344.45	640.00
10/20	205.00	459.60	769.50	232.00	501.70	882.00	107.50	345.70	670.00

Table 8. Testing Distributor Costs

	Kolmogorov Smirnov Sig.		**Variances**	**ANOVA**	**Bonferroni Sig.**	**(I) Group**	**(J) Group**	**Mean Difference (I-J)**
Mean_Dis	1	0.2	0.054	0.000	0.000	1	2	41.08917*
							3	116.53667*
	2	0.053			0.000	2	1	41.08917*
							3	157.62583*
	3	0.2			0.000	3	1	-116.53667*
							2	-157.62583*

The test results gave Kolmogorov–Smirnov significance values for the three groups greater than 0.05, indicating that the distributor cost data are normally distributed. Next, a homogeneity test and ANOVA were conducted, with variance significance values greater than 0.05, showing that the data are homogeneous. The ANOVA test revealed a significance value of less than 0.05, suggesting differences among the three data groups. The homogeneity test results were then followed by a Bonferroni post-hoc test.

The mean difference value in the bottom row of Table 8 shows that the average value of group 3 is 116.53 lower than group 1 and 157.62 lower than group 2. Based on the Bonferroni significance value, which is below 0.05, it can be concluded that there are significant differences among the three average distributor costs produced by the three scenarios.

A further comparison was made of the factory cost data as listed in Table 9, with the test results presented in Table 10. The results indicate that the factory cost data are normally distributed because the Kolmogorov–Smirnov significance values of the three groups exceed 0.05. The homogeneity test results, however, show a variance significance value of less than 0.05, indicating that the data are not homogeneous.

The ANOVA test yielded a significance value of less than 0.05, indicating differences among the three data groups. Based on the homogeneity test results, testing proceeded with the Games–Howell post-hoc test. The mean difference value in the bottom row of the post-test table shows that the average value of group 3 is 114.81 lower than group 1 and 147.55 lower than group 2. With a significance value below 0.05, it can be concluded that there are significant differences among the three average factory costs.

Table 9. Average Factory Cost Data

T/O	**Factory Cost w/o Strategy**			**Factory Cost w/ SMA**			**Factory Cost with EMA**		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1/5	222.50	448.78	712.50	237.50	482.02	822.50	122.50	335.00	592.50
1/10	200.00	448.91	780.00	225.00	483.51	777.20	110.00	334.31	577.50
1/15	212.50	450.25	857.50	240.00	481.85	812.50	120.00	333.54	602.50
1/20	220.00	448.88	742.50	230.00	482.53	807.50	117.50	334.02	577.50
5/5	205.00	450.44	755.00	222.50	480.46	842.50	97.50	335.58	642.50

5/10	195.00	451.09	785.00	257.50	481.38	767.50	85.00	335.04	615.00
5/15	205.00	448.64	735.00	240.00	480.82	797.50	117.50	335.20	615.00
5/20	197.50	449.10	795.00	217.50	484.09	807.50	110.00	334.64	615.00
10/5	200.00	451.65	737.50	230.00	483.45	797.50	125.00	335.78	592.50
10/10	200.00	449.66	805.00	240.00	482.79	815.00	132.50	334.26	615.00
10/15	232.50	449.07	832.50	240.00	482.46	767.50	100.00	334.13	640.00
10/20	200.00	447.35	722.50	230.00	481.37	760.00	107.50	334.54	590.00

Table 10. Testing at Factory Cost

		Kolmogorov Smirnov Sig.	**Variances**	**ANOVA**	**Games-Howell Sig.**	**(I) Group**	**(J) Group**	**Mean Difference (I-J)**
Fac_Mean	1	0.149	0.158	0.000	0.000	1	2	-32.74250*
							3	114.81500*
	2	0.2			0.000	2	1	32.74250*
							3	147.55750*
	3	0.2			0.000	3	1	-114.81500*
							2	-147.55750*

In terms of competition, this study provides data on the percentage of customers who shift to other retailers when consumer confidence declines. The percentage of customers who shift is listed in Table 11. Based on the average percentage of customers who shift, tests conducted include normality, homogeneity, ANOVA, and Post-Hoc Bonferroni tests, with the results shown in Table 12.

Table 11. Average Data on Percentage of Customers Shifts

T/O	**Shift Without Strategy**			**Shift with SMA**			**Shift with EMA**		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1/5	0.00	10.00	56.25	0.00	25.94	60.35	0.00	32.93	62.16
1/10	0.00	10.13	60.00	0.00	25.98	61.70	0.00	32.72	60.00
1/15	0.00	10.23	60.00	0.00	25.82	64.29	0.00	32.92	60.71
1/20	0.00	10.19	58.07	0.00	26.15	65.30	0.00	32.97	58.82
5/5	0.00	9.78	56.25	0.00	25.94	62.22	0.00	33.00	60.53
5/10	0.00	10.11	54.55	0.00	25.74	60.35	0.00	32.71	61.29
5/15	0.00	10.04	56.25	0.00	25.90	61.54	0.00	33.00	61.29
5/20	0.00	10.22	63.64	0.00	25.86	59.57	0.00	32.90	63.64
10/5	0.00	10.28	58.82	0.00	25.74	59.26	0.00	33.07	63.89
10/10	0.00	10.06	60.00	0.00	25.96	60.00	0.00	32.86	60.00
10/15	0.00	9.78	56.25	0.00	25.85	62.50	0.00	32.77	64.10
10/20	0.00	10.04	54.55	0.00	25.94	60.87	0.00	32.92	63.89

Table 12. Testing on the Percentage of Customers Shift

		Kolmogorov Smirnov Sig.	**Variances**	**ANOVA**	**Bonferroni Sig.**	**(I) Group**	**(J) Group**	**Mean Difference (I-J)**
Average_Move	1	0.172	0.456	0.000	0.000	1	2	-15.83000*
							3	-22.82583*
	2	0.16			0.00	2	1	15.83000*
							3	-6.99583*
	3	0.175			0.000	3	1	22.82583*
							2	6.99583*

Based on the Kolmogorov-Smirnov significance value of more than 0.05, it can be concluded that the data are normally distributed. The variance significance value in the homogeneity test, which is above 0.05, indicates that the data are considered homogeneous. The significance result of the ANOVA test is below 0.05, suggesting that there are differences among the three groups.

The next test is the Bonferroni Post-Hoc test, with results showing that the Bonferroni significance value is below 0.05. This indicates that there are significant differences among the three groups tested. The Bonferroni Post-Hoc test results in the top row show that the average value of group 1 is 15.83 lower than that of group 2 and 22.82 lower than that of group 3.

The next step is to summarize all the experimental results and calculate the averages, as shown in Table 13 below.

Table 13. Summary of Experiment Results

	Average Total Cost	**Average** Retailer Cost	**Average** Wholesaler Cost	**Average** Distributor Cost	**Average** Factory Cost	**Average Percentage of Customer Shifts**
Without Strategy	1810.81	472.36	427.48	461.48	449.49	10.07
SMA	1771.21	390.55	395.86	502.57	482.23	25.90
Single ES (EMA)	1163.07	184.10	299.35	344.94	334.67	32.90

Based on the results of the experiment and statistical analysis, research hypothesis H_1, which states that there is at least one group with a significantly different average financial performance, is accepted. Further testing with the Post-Hoc Test shows that the best financial performance is in BDG using the Single ES strategy.

The superiority of EMA can be theoretically explained through the mechanism of adaptive demand smoothing: EMA assigns exponentially decreasing weights to older observations, making it more responsive to recent demand fluctuations than SMA, which treats all historical periods equally. This responsiveness reduces the lag in order adjustments, thereby lowering both backorder accumulation and inventory excess. From a system dynamics perspective Sterman (2000), EMA dampens the amplification loop that drives the bullwhip effect by stabilizing the ordering signal at the retail level. This aligns with Syntetos (2016), who demonstrated that adaptive forecasting methods outperform static approaches in volatile supply chain environments.

Flexibility in order adjustments across units further supports findings by Strozzi (2007), confirming that differentiated unit-level ordering reduces aggregate system costs. To complement inferential findings, effect size was computed using eta-squared (η^2). The ANOVA for total cost yielded $\eta^2 = 0.43$, indicating a large practical effect Cohen (1988), suggesting that the choice of forecasting strategy explains approximately 43% of the variance in total operational costs. This magnitude of effect strengthens the practical significance of EMA superiority beyond statistical significance alone. Based on the values in Table 13 and the post-hoc test results, the Single ES (EMA) strategy achieves the lowest average total operational cost of USD 1,163.07, significantly lower than SMA (USD 1,771.21, $p < 0.05$) and no-strategy (USD 1,810.81, $p < 0.05$) groups. Unit-level costs under EMA are consistently lower: retailer (USD 184.10), wholesaler (USD 299.35), distributor (USD 344.94), and factory (USD 334.67).

Research based on simulation can support better business practices, as exemplified in the car sales business by General Motors (Sterman, 2000). The advantage of using simulation is the creation of a risk-free environment, allowing users to test variations of strategies and observe results without incurring losses. Another advantage is that trained users can adapt to new strategies when faced with hypothetical situations, such as a declining market or inflation. Additionally, simulations facilitate more efficient use of resources by visualizing the impact of each strategy on budgets, human resources, or commodities. This study also supports information sharing, in that consumer order data is used to rearrange retailer orders, reducing oscillations in

BDG and stabilizing the overall system (Lu, 2021).

Regarding the bullwhip effect, variance amplification ratios were examined across supply chain stages. Although EMA reduces order variance at the retail level compared to the no-strategy scenario, upstream variance (distributor and factory) remains elevated, indicating that the bullwhip effect is partially—but not fully—mitigated. This is consistent with Lu (2021) and Baisa (2024), who note that single-echelon forecasting interventions have limited propagation effects on upstream order volatility. Future studies should explore multi-echelon forecasting coordination to address this limitation (Ali et al., 2017). The role of information sharing in cost reduction is further confirmed by alignment with (Schnetzler & Schönsleben, 2007). From a managerial standpoint, these findings reveal a critical trade-off: while EMA reduces total operational costs, it simultaneously increases consumer shift rates (32.90%), indicating that pure cost optimization without service-level management may erode the customer base over time. Managers must therefore balance forecasting-driven cost efficiency with customer retention policies.

On the other hand, the EMA strategy has a weakness: the highest percentage of customers shift to competitors, at 32.90%. The increasing number of customer shifts tends to reduce consumer demand. Declining consumer demand causes total costs to be dominated by inventory costs at retailers because backlog costs decrease. With inventory costs valued at half of backlog costs, supply chain conditions tend to reduce total costs. Scenarios where inventory costs exceed backlog costs have been reported. Although this seems reasonable in simulations, it can negatively impact systems where revenue is calculated based on stock sales. In the T/O setting under the EMA strategy, the lowest total cost occurs at 1/20, indicating that inventory management relies on a large number of orders when inventory is at its minimum.

This research aligns with the stages of scientific inventory management by developing a model based on BDG in AnyLogic software. The model applies a management strategy combining information and data in BDG. The strategy determines when and how much stock to use in each unit to achieve optimal financial performance, rather than to hoard maximum goods. This also illustrates that scientific inventory management does not rely on emotional human decisions, which tend to be inconsistent and difficult to quantify.

Additional implications of these findings relate mainly to revenue aspects and managerial implementation in real supply chain systems. Since this model focuses on costs and does not yet include revenue functions, the cost efficiency generated by EMA strategies should be interpreted as operational performance rather than overall profit. In a real-world context, organizations implementing EMA-based forecasting need to complement it with customer retention policies and service-level management to ensure cost efficiency is not offset by declining revenue.

A key limitation of this study is that the financial performance metric is restricted to operational costs, excluding revenue dimensions. Therefore, the EMA advantage should be interpreted as operational cost efficiency rather than overall profitability. Future research should incorporate revenue functions to enable full profit-based performance evaluation. Decision-makers should complement EMA adoption with dynamic safety stock policies and customer loyalty programs to offset the consumer shift risk identified in this study. Furthermore, the findings suggest that EMA is most effective when combined with real-time visibility tools (e.g., demand sensing platforms) that enable rapid parameter recalibration in response to market shifts (Syntetos et al., 2016). In practice, EMA-based forecasting can be integrated into adaptive inventory planning systems at the retail level through real-time demand data pipelines. Successful implementation requires high-quality data governance, transparent model assumptions, and organizational capacity to interpret forecasting outputs.

CONCLUSION

EMA strategy is still able to provide the best financial performance compared to other scenarios through systemic cost control.This study developed a novel Beer Distribution Game (BDG) variant incorporating consumer trust dynamics and competitive demand response, simulated in AnyLogic with 5,000 replications. The primary finding is that the Single Exponential Smoothing (EMA) strategy achieves the lowest total operational cost efficiency among the three tested scenarios, demonstrating that adaptive, history-weighted forecasting can systematically reduce supply chain costs under competitive conditions.

Theoretically, this study extends BDG literature by demonstrating that consumer trust dynamics function as a behavioral competition mechanism that amplifies cost sensitivity. The EMA strategy contributes to system-level stability through simultaneous cost reductions across units, though its ability to fully mitigate the bullwhip effect remains limited at upstream echelons. Managerially, the findings highlight a cost-service trade-off: EMA reduces operational costs but increases consumer shift rates, necessitating complementary customer retention strategies.

In the context of bullwhip effect theory and behavioral operations, the EMA strategy functions as a historical data-based learning mechanism that reduces reactive and emotional ordering decisions. The use of EMA-based forecasting helps retail units respond to changes in demand in a more controlled manner, thereby reducing order variability compared to scenarios without the strategy. However, the existence of competition reinforces cost dynamics because a decline in service levels at one unit can trigger consumer shifts, which in turn affect demand patterns and cost distribution within the system.

Future research directions include: (1) integrating machine learning-based forecasting methods (e.g., LSTM, reinforcement learning) to compare against traditional EMA in dynamic BDG environments; (2) extending forecasting strategy implementation to multi-echelon levels (wholesaler, distributor, factory) to assess system-wide bullwhip mitigation; (3) incorporating revenue and profitability functions to enable comprehensive financial performance evaluation beyond cost efficiency; and (4) empirical validation of model findings using real supply chain operational data to enhance external validity. This study is limited by its exclusive focus on operational costs without revenue modeling, and the application of forecasting solely at the retailer level.

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AUTHOR CONTRIBUTION STATEMENT

Nengah Widiangga Gautama: Conceptualization, methodology, simulation model development, data analysis, visualization, manuscript drafting, and corresponding author responsibilities.

Tri Gunarsih: Research supervision, theoretical framework development, methodology validation, critical review, and manuscript editing.

Andi Harmoko Arifin: Data interpretation, statistical analysis validation, discussion development, and manuscript review.

Mursalim Nohong: Research supervision, conceptual refinement, critical evaluation of findings, manuscript revision, and final approval of the submitted version.

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