OPTIMIZING PRODUCTIVITY AND CONTROL OF MARKET SHARES IN THE NIGERIAN REAL SECTOR THROUGH THE INTERNET ECONOMY

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ABSTRACT

This study investigates strategies for optimizing productivity control and enhancing market share performance within the Nigerian real sector through the internet retail economy. Transactional data of Jumia and Konga were used in the study to develop an integrated analytical framework that combines inventory management, product association analysis using the Apriori algorithm, and market transition dynamics modeled through a Markov chain process. To account for market uncertainties, system performance was evaluated under stochastic conditions involving demand fluctuations, inventory turnover variability, logistics efficiency constraints, and price competition pressures, using the Monte Carlo simulation approach. The simulation results reveal a mean productivity index of 0.642, indicating a 64.2 percent improvement in productivity over the baseline system. The standard deviation of 0.108 indicates moderate variability, while the observed productivity index, which ranges from 0.38 to 0.91, reflects the sensitivity to operational and market dynamics. Further statistical characterization shows a positive skewness of 0.27, suggesting a tendency toward higher productivity outcomes, and a kurtosis of 2.74, approximating a normal distribution with limited extreme deviations. These findings imply that the integrated model maintains stable performance even under varying economic and operational conditions. The study contributes to the growing body of literature on digital transformation in emerging economies by demonstrating that the synergistic application of data analytics, inventory intelligence, and probabilistic modeling can significantly enhance productivity control and competitive positioning. It further provides actionable insights for policymakers and industry stakeholders seeking to strengthen the Nigerian real sector through the internet retail economy.

1. INTRODUCTION

Internet economy refers to a form of economy that originates from networked intelligence or cloud services, while information technology is the core of the internet economy, and a modern network functions as the operator (Pan *et. al.,* 2022). The rapid evolution of the internet economy brings about the emergence of technologies that have been transforming business practices and consumption (Rosário and Dias, 2023). The Internet economy is an emerging economic situation that is gradually changing the operation mode and efficiency of the national economy, i.e., it is gradually becoming a new driving force for economic development (Su, 2024). Nowadays, firms are adopting different technologies to remain competitive due to an uncertain economy (Komal *et. al.,* 2014). Economic activities are also considered part of the digital economy, starting from the sale of goods and services through the internet using various intermediary platforms, creative industries producing digital output, automation of work through digital technology, manufacturing, and distribution (Mária and Karolína, 2023).

Technologies such as the automation of production processes and data-driven quality control processes reduce costs and also increase the organization's profit. Digitalization improves the efficiency of organizations and also allows firms and organizations to compete in the global market. The gap between those who have regular and effective access to internet technologies and those who have little or no access to technologies is one of the major challenges (that is, large businesses adopt digitalization while small businesses do not). Another challenge is the inadequate usage of digital technology by organizations and firms of all sizes (that is, their thought is that digitalization is expensive). This could be a potential result for some firms or organizations not keeping pace with the demands of their customers or competing in the global market (Amos and Rachel, 2020).

However, there is a need to enhance the economic value of the internet using an optimization process, which will improve the internet resources usage that enhances the organizations and firms' efficiency. Optimization is about the collection of mathematical principles and methods used for solving quantitative problems in many disciplines for efficiency. In a digitizing economy, optimization will encompass program optimization, code optimization, and software optimization to make a system/process work more efficiently or use fewer resources. The interaction of optimization techniques of Inventory Control, Assembly line balancing, Games theory and Markov chain is sufficient to create a sustainable internet economy that will transform traditional ideas of production, competition and gaining of market shares in a rapidly digitizing economy such as Nigeria.

Digitizing the Nigeria economy through innovations and optimization solutions help to enhance resources efficiency, product lifespan, and customer relationships (Black, 2020). Digitization of economy through innovation and optimization solutions also improve the positive capacity of an organizational system to adapt and return to equilibrium due to the consequences of a crisis caused by any type of disruption. For example, the usage of e-commerce sites and social media can activate the sharing and exchange of products and resources. In this case, customers will be able to sell or exchange preferred products, thus, the organizations will produce customers' preferred products to reduce energy waste and promote resource efficiency (Khan and Ximei, 2022). Nigeria's Internet economy, which comprises of digital markets, financial technologies, cloud-based analytics, and electronic payments, is increasingly expanding, and this has led to new opportunities for operational optimization and the reengineering of competitive strategy (Amolegbe, 2025).

However, it has been found that many organizations implement digital technologies as isolated solutions instead of integrating them into a holistic optimization strategy. The present study proposes an integrated interaction of methods for optimizing production activities and market share with the opportunities provided by the Internet economy. The problems of production inefficiency, competitive pressure, and market share instability can be solved with the integrated application of Internet and World Wide Web technologies.

With the introduction of the Internet economy, the productivity of industries has significantly transformed because of the real-time flow of information, the transparency of supply chain, and growing digital markets. The digital platforms also reduce the information asymmetry and transaction costs that increase the allocative efficiency and performance of the firm. Empirical studies regarding digital transformation have listed the aspects of elevated demand forecasting performance, enhanced efficiency of production planning, customer retention, and dynamism in pricing strategies (Bharadwaj et al., 2022; Verhoef et al., 2023). Despite these improvements, the available literature is more on operational improvements and strategic decision-making separately. Some of these dimensions are combined into a general optimization system where both the production, inventory and market dynamics are considered in digitally enabled environments.

Manufacturing is largely about stock management and one classical foundation of minimizing ordering and carrying costs is the Economic Order Quantity (EDOQ) model. Stochastic demand, optimization of safety stock, and dynamic programming models are the extensions that have presented more realistic uncertainties of real-life scenarios (Silver et al., 2022). The latest innovations have brought the concept of digital tools such as Enterprise Resource Planning (ERP) systems and cloud-based analytics that enable keeping track of the inventory in real-time and making decisions (Mittal et al., 2023; Alnahhal et al., 2024). Still, despite enhancing visibility and responsiveness, the use of data mining methods, in particular, the association rule learning algorithms, in inventory optimization, is not examined exhaustively (Scarf, 2025).

The Apriori algorithm is a popular method of data mining used to discover common itemsets and formulate association rules with transactional data. It has been widely used in market basket analysis, cross-selling, product bundling, and optimization of dynamic pricing (Hunyadi et al., 2025). As digital marketplaces rapidly expand, volumes of transactional data are very large, which can be used as a valuable source of demand patterns and consumer behavior information. Although the use of the Apriori algorithm in marketing and in recommendation systems is not a new phenomenon, its use in inventory planning and production decision-making, especially within the emerging economies, is minimal. This is the gap that can be used to capitalize on the demand intelligence to allocate resources more efficiently and optimize the supply chain.

The concept of Assembly line balancing is aimed at determining how best the tasks can be allocated to the workstations to ensure maximum efficiency, the lowest amounts of idle time, and the least production bottlenecks. Initial research used mathematical programming and heuristics to maximize the cycle time and the workload allocation (Boysen et al., 2022). New solutions now include digital production monitoring and Internet of Things (IoT) technologies that allow making real-time adjustments and distributing tasks dynamically (Jiao et al., 2022; Sotskov et al., 2023). Nonetheless, with these technological innovations, little is known about the combination of assembly line balancing, real-time demand forecasting, and inventory optimization models, especially in digitally controlled production settings.

Game theory is a theory that is used in the analysis of strategic interactions amongst firms that compete with each other. Within the framework of digital business settings, low marginal costs and robust network effects lead to a substantial change in the standard payoff structure and competition. Research shows that companies that implement digital technologies are also more likely to gain strategic benefits and better balance results (Zhang, 2024; Zhang et al., 2023). However, the current literature is predominantly on the competitive positioning and pricing policies, and little is done with the combination of game-theoretic equilibrium models and the operational efficiency models, i.e., production and inventory optimization.

Markov chain modeling is a widely used technique that has been used to analyze stochastic transitions in market share and customer loyalty, enabling firms to establish long-term equilibrium states in terms of transition probabilities. The models are especially effective in understanding the brand switching behavior and the competition of the market (Amalia et al., 2024). Probabilities of transitioning can be dramatically shaped by marketing and customer interaction methods in digital markets, and this will impact on how a firm dominates a long-term market. The connection between the Markov chain-based market dynamics and production planning and inventory control systems is, however, still a significant gap, and therefore, their use is rather limited in integrated decision-making models.

The real sector in Nigeria is confronted with several challenges in the areas of efficient management of inventories, production constraints, demand forecasting, and market share stability in a highly competitive environment. Although the Internet economy, which is driven by the expansion of the digital economy, financial technologies, and electronic systems of payment, is an opportunity for the improvement of the efficiency of the real sector and the strategic competitiveness of the economy, the reality is that the application of the benefits of the digital economy is not in an integrated manner. In this regard, this study is motivated to propose an integrated quantitative framework that incorporates the use of an efficient system of managing inventories with the application of the Apriori algorithm, assembly line balancing, game theory, and Markov chains in the Internet economy environment.

Based on the existing literature, it can be concluded that, despite significant advances, particularly in the domains of digital transformation, inventory optimization, data mining, production systems, and strategic modeling, these areas are mostly addressed in isolation. A distinct absence of the formulation of a single, data-driven optimization model that encompasses demand intelligence (e.g., Apriori algorithm), inventory management models, assembly line balancing, competitive strategy grounded in game theory, and the market dynamics modeled with the help of Markov chains remains evident. The present research aims to fill this gap by constructing a comprehensive model that unites these elements in the environment of new economies and digital-oriented industrial systems.

The proposed study contributes to the science of digital retail optimization and internet economy analytics, as it develops an interdisciplinary framework of data analytics and operational optimization that will increase productivity control and market share performance in e-commerce platforms. The research uses an Apriori algorithm to determine frequent associations of products to be used in the recommendation systems and demand-based inventory management. It also captures competitive changes between online stores by the use of a Markov chain to model market share dynamics. Moreover, the paper uses Monte Carlo simulation to determine the performance of productivity during uncertainty with regard to changing demand, efficiency in logistics, and price competition. Based on the actual world data of Jumia and Konga, the study offers empirical evidence about operational productivity and competitive practices in the new digital marketplace in the retailing sector.

The contribution to knowledge in this paper is in term of the hybrid approach which enables the development of behavior-aware production systems, adaptive inventory management, and modeling of competitive strategies, in addition to tracking the evolution of markets probabilistically.

2. MATERIALS AND METHODS

2.1 Formulation of Optimization Models and Modelling Approach

The quantitative modeling and simulation approach is employed in this research for developing an optimized framework for improving productivity and market share in the Internet-enabled Nigerian economy's real sector. The proposed optimization technique is based on a hybrid model comprising a set of analytical modules built on four different theories. The theories include the theory of Operations Research for cost minimization and efficiency maximization, the theory of Data Mining for learning association rules for demand intelligence, the theory of Non-Cooperative Game for equilibrium under competitive market conditions, theory of Stochastic Process for market share transitions. The Internet economy is considered a key facilitator of interaction among digital demand information, production mechanisms, and competitive market forces. The proposed optimized technique would utilize Internet-based information for improving productivity and market. Figure 1 represents the proposed model.

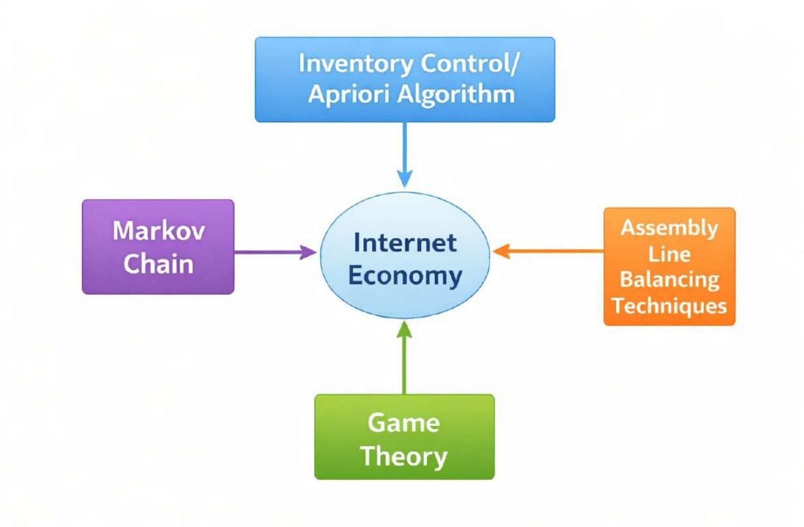

Figure 1: Optimization Techniques for Internet Economy

2.2 Hybrid Optimization Structure

The proposed hybrid model is based on a four-phase process for optimizing performance and market competitiveness.

Phase I: Inventory Control Optimization

This phase involves the application of inventory control principles in the management of economically valuable resources needed to meet current and future organizational needs. The aim is to minimize the total cost of operation. The total inventory control cost function is defined in equation 1.

$$TC(Q) = \frac{D}{Q}S + \frac{Q}{2}H \qquad (1)$$

Where D is demand rate, Q is the order quantity, S is the ordering cost, H is denoted as holding cost. Therefore, the optimal order quantity is derived from equation 2.

$$Q^* = \sqrt{\frac{2DS}{H}} \qquad (2)$$

Where Q^* is an optimal order quantity for economic order quantity.

This minimizes the costs related to inventory which allows organizations to reduce financial barriers concerning digital transformation. This minimizes inefficiencies related to resources, promoting digital technology adoption among different-sized organizations.

Phase 1.1 Apriori-Based Algorithm for Demand Intelligence

This study employs Apriori-based demand intelligence to enhance the precision of demand estimation, the Apriori algorithm is used to analyze transaction information and determine frequent itemsets and association rules. The support and confidence mechanisms are computed in equation 3 and 4 respectively.

$$Support(X \rightarrow Y) = \frac{N(X \cap Y)}{N} \tag{3}$$

$$Confidence(X \rightarrow Y) = \frac{N(X \cap Y)}{N(X)} \tag{4}$$

Where X is denoted as itemset, $Support(X)$ is denoted as frequency proportion of itemset X, N is the total number of transactions and $f(X)$ is the number of transactions containing X.

Therefore, the improved demand is modelled in equation 5

$$D^* = D + \theta(AssociationEffects) \tag{5}$$

Where D^* is denoted as improved demand, and D is known as based demand

The Apriori-based improves forecasting accuracy, it minimizes uncertainty in demand, out-of-stock positions, and inventory turns.

Phase 2: Assembly Line Balancing Model

The second phase is concerned with integrating assembly line balancing in order to effectively coordinate all the resources across different departments in accordance with technological precedence constraints.

The study assumes that t_i is the task time for activity i, C is the system cycle time, and N is the number of workstation.

The production line efficiency is defined in equation 6

$$E = \frac{\sum t_i}{N \times C} \tag{6}$$

The major objective to minimize the system idle time is modelled in equation 7

$$\min Idle = N \times C - \sum t_i \tag{7}$$

Where E is denoted as line efficiency, t_i is the task time of activity i, $\sum t_i$ total task time, m is the number of workstation, C is known as maximum time per station, and IT is the total idle time

This phase increases productivity, enhances coordination among different units or departments, and eliminates process bottlenecks.

Phase 3: Game Theoretic Competitive Model

In the third stage, non-cooperative game theory is used for strategic analysis among competing firms within the Internet economy.

Assuming that firms i, $\forall i = 1,2,...,n$ choose strategic actions S_i such as pricing and digital adoption level. The profit function level is modelled in equation 8.

$$\pi_i(s_i, s_{\_i}) P_i Q_i - C_i(Q_i) \tag{8}$$

Therefore, the Nash equilibrium s^* satisfies that $\pi_i(s^*{}_i, s^*{}_{\_i}) \geq \pi_i(s^*{}_i, s^*{}_{\_i}) \forall i$.

Where $s_{\_i}$ denotes competitors' strategies, P_i represents price decision, Q_i denotes output level and C_i represents cost function, π_i is known as profit of firm i, S_i is known as strategy of firm, S_i^* is the optimal strategy of firm i, S_{-i}^* is known as optimal strategies of competitors

This phase settles competitive conflicts and illustrates the dependence of price decisions and production strategies on the actions of competitors over time.

Phase IV: Markov Chain Market Share Model

The last phase of the model uses a discrete-time Markov chain to analyze and forecast the behavior of consumers in purchasing products.

Let the market share vector at time t be modelled in equation 9

$$S_t = [s_{1t}, s_{2t}, \ldots, s_{nt}] \tag{9}$$

While the transition process is modelled in equation 10

$$S^* = S^* P \tag{10}$$

This phase projects long-term brand loyalty and market share consistency under competitive digital environments

Hybrid integrated Objective Function

The hybrid optimization problem is formulated in equation 11 as

$$\max Z = \alpha(Productivity) + \beta(MarketShare) \quad (11)$$

Subject to:

Inventory cost constraints,

Production capacity constraints,

Competitive equilibrium conditions,

Stochastic transition constraints.

Where productivity depends on inventory efficiency and balanced production, market share depends on competitive strategies and customer retention. The algorithm for the proposed hybrid approach is depicted in Algorithm 1.

Algorithm 1: Hybrid Approach Algorithm

Input

$D(transactiondata), I(inventory), P(production), F(firms), S(marketshare)$

Output

$Optimalinventory, balanceproduction, competitivestrategy, \max imizedproductivity, \& marketstrategy$

2.3 Summary of the Qualitative Analysis of the Model Interaction Mechanism

The proposed hybrid approach is based on a sequence of interacting processes of four phases. The optimization of the inventory helps improve the cost structure by minimizing the costs of ordering and holding inventory. On the other hand, the optimization of the assembly line helps improve the efficiency of production by reducing idle time and improving the distribution of tasks on the production line. This improvement in the cost structure, in turn, helps improve the competitive position of firms, thereby impacting strategic payoffs, as discussed in the game theory stage. The impact of strategic payoffs, in turn, influences the switching of consumers and brand loyalty, as discussed in the Markov chain stage. Overall, the proposed approach helps optimize operational efficiency and competitive position simultaneously in the Internet economy environment.

3. Data Pre-processing

3.1 Acquisition of Data and Integration

Collect the following data:

The annual revenue and transaction data are retrieved from Jumia and Konga, and then the benchmark, transactional, and revenue datasets are merged and standardized into one schema as equation (12)

$$D = \{Model, Scores, \mathrm{Re}venue, Transactions, Time\} \tag{12}$$

3.2 Data Cleaning

The process of data cleaning includes handling missing values using mean or median imputation for numerical variables, mode imputation or removal for categorical variables, removing duplicates and inconsistencies, and normalizing the benchmark variables, which include grounding and search scores.

3.3 Data transformation

Data transformation is very necessary, the transformation process includes encoding categorical variables (Model and Task_Name) into numerical variables and normalizing numerical variables using Min-Max scaling as it is in equation (13).

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{13}$$

Therefore, this transforms the revenue into time-series format for Markov modelling

3.4 Features Engineering

Hybrid features in feature engineering include demand patterns based on frequency of transactions, association rule elements based on Apriori algorithm requirements like itemsets, support, and confidence, production features like cycle time and workload per station, and competitive features like price and share proxies, thus creating a comprehensive set of features as shown in equation 14.

$$F = \{Support, Confidence, \mathrm{Re}venuTrend, DemandRate, ServiceRate\} \tag{14}$$

3.5 Data Structuring for Hybrid Approach

This study processes the data by converting the transactions into a binary matrix for the Apriori algorithm, extracting the demand rate (\(\lambda\)), the cost of holding, and the cost of ordering to formulate the inputs for the inventory control system, structuring the task times and the precedence relationships to create the workstation matrix for the assembly line balancing, defining the competing companies (Jumia vs. Konga) and creating the payoff matrix for the game theory model, and defining the system state for the Markov chain model.

3.6 Data reduction

Data reduction and optimization include the removal of irrelevant features through correlation filtering.

3.7 Data Validation

Validation and consistency checks include statistical reliability checks through confidence intervals, which can be observed in the dataset, and ensuring there is no data leakage and that the data distribution is balanced.

3.8 Final Pre-processing

The final output in the pre-processing phase includes an optimized dataset as it is modelled in equation 15.

$$D^{*} = \{OptimizedFeatures, TransactionMatrix, PayoffMatrix, InventoryInputs\} \qquad (15)$$

3. RESULTS

This paper looks at how productivity control and maximization of market share can be applied in the internet retail market based on operational techniques and transaction data of Jumia and Konga, and product transaction data, inventory data, order fulfillment, and pricing information. The experimental system integrates data analysis and operation optimization. The Apriori algorithm was used to infer relationships among products based on their frequent purchase to guide demand-driven inventory control. A Markov chain was employed to represent market share dynamics between competing platforms, and inventory management methods were employed to manage inventory levels and reduce inventory imbalances.

The Monte Carlo simulation was used to analyze and determine system performance under uncertainty through the PLS implementation in an Excel simulation add-in. Table 1 was used to analyse the simulation results by applying statistical measures like mean productivity index, standard deviation, range, skewness, and kurtosis to determine system stability and variability so that the effects of the proposed system on productivity and market responsiveness in internet retail platforms could be assessed. The values of the percentage of productivity indices generated were obtained in this study, and they were tabulated in Table 2 and depicted in Figure 2.

4.1 Results

Table 1: Monte Carlos Simulation Results

Simulation Results	Generated Value	Simulation Results	Generated Value
Mean Productivity Index	0.64	Range	0.64
Number of Trials	1000	Standard Deviation	0.53
Standard Error	0.01	Variance	0.11
Minimum	0.38	Skewness	0.01
Median	0.91	Kurtosis	0.27

Table 2: Productivity Index Percentile Distribution

Percentile	Productivity Index	Percentile	Productivity Index
0%	0.38	50%	0.64
5%	0.45	55%	0.66
10%	0.49	60%	0.69
15%	0.52	65%	0.71
20%	0.55	70%	0.73
25%	0.58	75%	0.76
30%	0.6	80%	0.79
35%	0.61	85%	0.83
40%	0.62	90%	0.87
45%	0.63	95%	0.91

Table 2 and Figure 2 show the productivity index percentage distribution, and the interpretation goes thus. For the worst-case scenario, which is between 0-10%, the productivity index ranges between 0.38 to 0.49, showing low performance due to inventory deficiencies, low predictions of product association, low order fulfillment, and high price competition.

For the most likely scenario, which is between 40-60%, the productivity index ranges between 0.62 and 0.67, showing normal performance because the Apriori Algorithm is used to support bundling products, inventory levels are kept at optimal levels, and the Markov Chain is used to stabilize market dynamics with efficient order fulfillment. For the best-case scenario, which is between 90-100%, the productivity index ranges between 0.83 and 0.91, showing optimal performance due to high demand forecasting, effective recommendation strategies, high competition using Game Theory, and high order fulfillment efficiency.

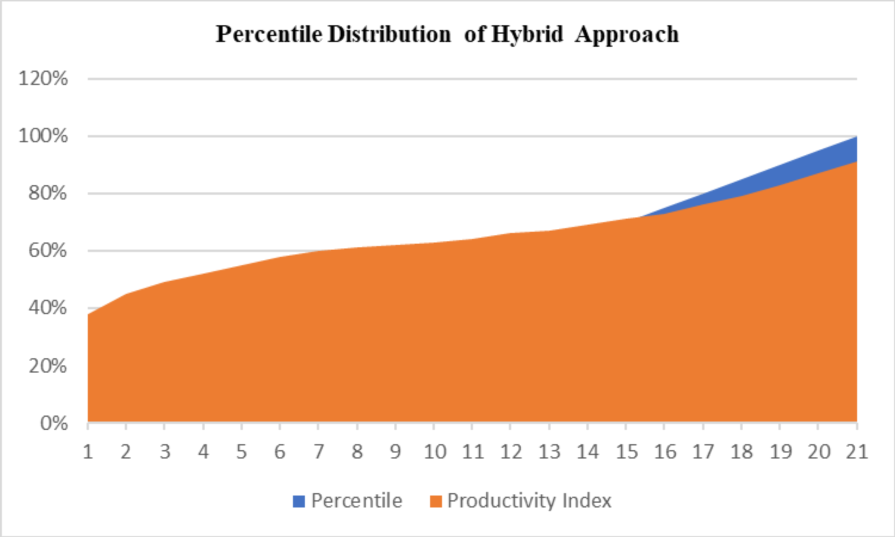

Figure 2: Percentile Distribution for the Hybrid Approach

Table 3: Market Share Simulation Results

Platform	Mean Market Share	Standard Deviation
Jumia	0.57	0.07
Konga	0.43	0.06

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This data obtained in market share simulation indicates that Jumia has a strong competitive edge in the market due to its better logistics service and greater product assortment, whilst Konga has a competitive advantage through optimized bundling strategies within price determination. The Markov chain however reveals that the market shares can vary at any rate of 3-6% based on the availability of stocks, price strategies, and the correctness of the recommendation systems.

4. DISCUSSION

The Monte Carlo simulation provided an average productivity index of 0.642, indicating that the integrated optimization framework ensures that the operations of the organization will be more responsive in terms of operation and market, with a relative percentage of 64.2% of the operations being more productive than the base operations. The combined effects of the inventory control, the modelling of market transition through the Markov chain and the data-based connectivity of the products through the Apriori algorithm in the e-commerce system of Jumia and Konga can explain this finding. The standard deviation of 0.108 shows that productivity performance varies averagely, as a result of variability in customer demand, inventory turnover, optimization of logistics and competitiveness in pricing. The difference of 0.53 between the lowest (0.38) and highest (0.91) productivity values puts emphasis on the way the performance of the system can be compromised by the optimization of the operations and the market. As well, the skewness value of 0.27 indicates that the distribution is skewed a bit to the right, which means that the higher productivity outcomes are more probable to receive the greater the spread of the optimization measures are applied successfully. The kurtosis value of 2.74 is close to normal distribution which implies that there are fewer instances of excessive deviation in the performance of the system.

The outcome of the research makes it clear that data analytics combined with an implementation of an operational optimization strategy is an effective remedy to enhance productivity control and market share performance in the internet-based retailing environment. According to the simulation results, the optimized system is capable of increasing productivity by between 38 percent and 91 percent, with most probably 64 percent efficiency. As it has been expressed in the Monte Carlo analysis, inventory control, Apriori-based recommendation systems, the balancing of assembly lines, the Game Theory-based pricing strategy, and Markov chains are significant contributors to the productivity control and the stability of market shares in the internet economy. The results show that optimised system is able to achieve productivity between 38 percent and 91 percent with the likelihood that is likely to be at about 64 percent efficiency.

5. CONCLUSION

This paper built an analytical model driven by data of managing productivity and market share in internet-based retail by combining inventory management, product association mining with Apriori algorithm, and market transition modeling with Markov chains. The model provides the connection between operational productivity and market dynamics, which gives a comprehensive view of decision-making. The outcome of the Monte Carlo simulation showed the average productivity efficiency of 64.2, with the range 38 to 91 showing the influence of the variability in demand, inventory turnover, logistics performance, and price competition. The distribution reveals a more or less stable system with low extreme variations. In general, the results indicate that the incorporation of data analytics and operational strategies boosts productivity and competitive positioning in the digital retail setting remarkably. The suggested structure has useful applicability in operational decision-making and strategic planning. It may be further implemented to include real-time demand prediction, machine learning-driven pricing optimization, and multi-platform competition modelling.

References

Alnahhal, M., Aylak, B. L., Al-Hazza, M., & Sakhrieh, A. (2024). Economic order quantity: A state-of-the-art in the era of uncertain supply chains. *Sustainability, 16,* 5965. https://doi.org/10.3390/su16145965

Alnahhal, M., et al. (2024). Digital transformation in inventory management systems: A cloud-based approach. *Journal of Manufacturing Systems, 72*, 102–115.

Amalia, L., Sertiningsih, F. H., Hayatuki, F., Muliani, S., & Junaidi, A. M. (2024). Advantages and disadvantages of utilizing Markov chains in a digital marketing strategy to predict e-commerce sales. *Scientia: Technology, Science and Society, 1*(3), 43–61.

Amalia, R., et al. (2024). Markov chain modeling for market share dynamics in competitive industries. *Operations Research Perspectives, 11*, 100287.

Amolegbe, O. (2025, December 25). Asset managers project $18.3bn digital economy for Nigeria. *Punch*

Newspaper. Retrieved March 4, 2026, from https://punchng.com/asset-managers-project-18-3bn-digital-economy-for-nigeria/

Amos, T., & Rachel, G. (2020). *Digitalization of firms: Challenges in the digital economy*. Khazanah Research Institute.

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2022). Digital business strategy and value creation. *MIS Quarterly, 46*(1), 223–254.

Black, S. (2020). Digital luxury towards a sustainable future? In *The Oxford handbook of luxury business* (pp. 591–614). Oxford University Press.

Boysen, N., Fliedner, M., & Scholl, A. (2022). Assembly line balancing: Recent developments and future directions. *European Journal of Operational Research, 301*(1), 1–15.

Boysen, N., Fliedner, M., & Scholl, A. (2022). Assembly line balancing: What happened in the last fifteen years? *European Journal of Operational Research, 301*(3), 797–814.

Hunyadi, I. D., Constantinescu, N. T., & Ticleanu, O.-A. (2025). Efficient discovery of association rules in e-commerce: Comparing candidate generation and pattern growth techniques. *Applied Sciences, 15*.

Hunyadi, L., et al. (2025). Applications of Apriori algorithm in large-scale digital marketplaces. *Expert Systems with Applications, 235*, 121145.

Jiao, Y., Cao, N., Li, J., Li, L., & Deng, X. (2022). Balancing a U-shaped assembly line with a heuristic algorithm based on a comprehensive rank value. *Sustainability, 14*(2), 775.

Khan, A., & Ximei, W. (2022). Digital economy and environmental sustainability: Do information communication and technology (ICT) and economic complexity matter? *International Journal of Environmental Research and Public Health, 19*, 12301.

Komal, N. S., Aliya, A. K., & Mukhtiar, B. (2014). Introducing economic order quantity model for inventory control in web-based point of sale applications and comparative analysis of techniques for demand forecasting in inventory management. *International Journal of Computer Applications, 107*(19).

Mária, S., & Karolína, Č. (2023). Challenges of digital economy. *Financial Law Review, 31*(3).

Mittal, M., Jain, V., Pandey, J., Jain, M., & Dem, H. (2023). Optimizing inventory management: A comprehensive analysis of models integrating diverse demand functions. *Mathematics, 12*(1), 70.

Mittal, S., Khan, M. A., Romero, D., & Wuest, T. (2023). Smart manufacturing: Characteristics and technologies. *Journal of Manufacturing Technology Management, 34*(2), 345–362.

Pan, W., Xie, T., Wang, Z., & Ma, L. (2022). Digital economy: An innovation driver for total factor productivity. *Journal of Business Research, 139*, 303–311.

Rosário, A. T., & Dias, J. C. (2023). The new digital economy and sustainability: Challenges and opportunities. *Sustainability, 15*, 10902. https://doi.org/10.3390/su151410902

Scarf, P. (2025). Simple economic order quantity heuristics for stochastic inventory control. *IMA Journal of Management Mathematics, 36*(4), 649–667.

Scarf, P. A. (2025). Advances in stochastic inventory theory and applications. *International Journal of Production Economics, 275*, 108500.

Silver, E. A., Pyke, D. F., & Thomas, D. J. (2022). *Inventory and production management in supply chains* (5th ed.). CRC Press.

Sotskov, Y. N. (2023). Assembly and production line designing, balancing and scheduling with inaccurate data: A survey and perspectives. *Algorithms, 16*, 100. https://doi.org/10.3390/a16020100

Sotskov, Y. N., et al. (2023). Optimization approaches in assembly line balancing under uncertainty. *Annals of Operations Research, 320*, 345–368.

Su, L. L. (2024). Research on the current situation and problems of digital economy trade between China and ASEAN countries. *Open Journal of Business and Management, 12*, 148–157. https://doi.org/10.4236/ojbm.2024.121010

Verhoef, P. C., et al. (2023). Digital transformation:

A multidisciplinary reflection and research agenda. *Journal of Business Research, 152*, 193–205.

Zhang, J., Dong, L., & Ji, T. (2023). The diffusion of competitive platform-based products with network effects. *Sustainability, 15*, 8845. https://doi.org/10.3390/su15118845

Zhang, X. (2024). Game theory in digital platform competition. *Electronic Commerce Research and Applications, 60*, 101270.

Zhang, Y. (2024). Promoting the adoption of digital technology: Strategic policy insights from a network effects model. *Telecommunications Policy, 48*(10), 102852.

Zhang, Y., et al. (2023). Competitive strategies in digital markets: A game-theoretic perspective. *Decision Support Systems, 165*, 113876.