Economics

BIG DATA ANALYTICS FOR DEMAND FORECASTING: INSIGHTS AND PRACTICES IN GLOBAL AND AZERBAIJAN MARKETS

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Abstract. This article examines the critical role of advanced inventory management and demand forecasting techniques within the retail sector of Azerbaijan, set against a backdrop of rapid market changes and economic fluctuations. Traditional methods relying on historical data often fall short in addressing the dynamic nature of consumer demand. By leveraging Big Data analytics, businesses can uncover significant patterns through modern methodologies like machine learning, exponential smoothing, and linear regression, enabling more precise forecasting than conventional approaches. Advanced Tools of Microsoft Excel, such as Power BI, play a vital role in this transformation, allowing companies to analyze real-time data and make informed decisions aligned with market trends. However, the adoption of these advanced technologies comes with challenges, including data integration issues and the need for employee training. Despite these hurdles, the integration of Big Data tools is essential for retail companies in Azerbaijan to enhance operational efficiency and profitability. This article highlights the importance of refining demand forecasting practices to improve inventory management and supports the development of innovative strategies that can better respond to consumer needs in a competitive landscape. Ultimately, it emphasizes that effective adoption of analytics can significantly boost market performance and business resilience.

Keywords: *Azerbaijan, Demand Forecasting, Big Data Analytics, Inventory Management, Supply Chain.*

Introduction

In today's fast-paced markets, inventory management is key to balancing product availability and costs. Traditional forecasts based only on historical data often fail under rapid economic change, as seen in Azerbaijan, where retail still faces mismatches between production and consumption.

Big Data analytics is transforming inventory management and demand forecasting. Using large datasets and tools such as machine learning, exponential smoothing, moving averages, simple linear regression, Power BI, and advanced Excel, companies can work with near real-time data, reveal patterns, and achieve more accurate forecasts than with traditional seasonal models. These tools help Azerbaijani retailers collect, process, and visualize data, improving understanding of market dynamics and supporting data-driven decisions.

However, adopting these technologies brings challenges: integrating data from different systems, training employees, and ensuring data quality, since errors in source data cause incorrect forecasts.

Despite these issues, using Big Data tools is essential for Azerbaijani businesses to stay competitive. Data-driven forecasting improves operational efficiency, aligns inventory with changing demand, and supports profitability and stronger market positions. As Big Data technologies advance, companies can further increase forecasting accuracy, react faster to market shifts, and enhance their competitive edge.

Research Objective

The primary objective of this research is to examine how Big Data analytics can improve demand forecasting accuracy in Azerbaijan's retail sector. It analyzes techniques such as machine learning, statistical methods, and their integration with tools like Power BI and advanced Excel to identify best practices for more accurate demand predictions. The study reviews current forecasting methods in retail using quantitative data from sales records and consumer behavior, compares them with global benchmarks, and offers practical recommendations for Azerbaijani retailers to optimize inventory management and better align with market demand.

Advances in data collection and analytics now enable more precise demand forecasting. Big Data has become a key part of decision-making, especially thanks to real-time and low-latency monitoring of business events. This research uses retail datasets with weekly, monthly, and annual sales from different companies for 2015–2024, providing insight into consumer behavior and demand patterns over time. The study focuses on seasonality, promotion effects, and regional differences, all crucial for inventory optimization. Including small and medium-sized enterprises (SMEs) ensures that the results are relevant to a wide segment of the Azerbaijani retail market and help identify strategies to improve forecasting accuracy and operational efficiency.

Problem Statement

In today's fast-paced markets, inventory management is essential for balancing product availability and cost control. Traditional forecasting methods based only on historical data often fail under rapid economic and market changes, as seen in Azerbaijan, where the retail sector still faces mismatches between production and consumption.

Big Data analytics is transforming inventory management and demand forecasting. By using large datasets and methods such as machine learning, exponential smoothing, moving averages, and simple linear regression, companies can work with near real-time data, identify patterns, and improve forecast accuracy compared with traditional seasonal models. Tools like Power BI and advanced Excel help Azerbaijani retailers collect, integrate, process, and visualize data, providing a clearer picture of market dynamics and supporting data-driven decisions aligned with consumer trends.

However, the transition to these tools creates challenges: integrating data from different systems, training employees to use advanced features, and ensuring high data quality, since errors in source data lead to unreliable forecasts.

Despite these difficulties, adopting Big Data tools is vital for Azerbaijani businesses to remain competitive, improve operational efficiency, and align inventory strategies with changing demand.

Problem-solving methods and Approbation

This article outlines various problem-solving methods utilized in demand forecasting, emphasizing traditional statistical techniques, Integration with Microsoft Excel advanced tools, machine learning, and AI technologies. These methodologies offer structured approaches to analyzing data and predicting consumer demand.

Traditional statistical methods, such as Simple Linear Regression, Moving Average, and Exponential Smoothing, provide foundational tools for understanding historical sales patterns. Simple Linear Regression predicts demand (Y) based on influential factors (X), while Moving Average and Exponential Smoothing help identify underlying trends by reducing short-term fluctuations.

Leading organizations, such as "Danone" and "IDS Borjomi Georgia", apply these problem-solving methods to refine their forecasting processes. Danone utilizes the SAP planning tools and Microsoft Excel advanced tools to enhance its forecasting capabilities in the dairy market, allowing for swift supply chain adjustments. Borjomi employs Microsoft Dynamics, JDA, and Power BI for advanced statistical techniques and AI, aligning its demand forecasting with consumer preferences [Author].

Demand Forecasting Calculation Techniques:

Simple Linear Regression:

$$[\ Y = a + bX\ ] \tag{1}$$

Explanation:

(Y) represents the predicted demand that we seek to estimate based on past data.
(a) is the Y-intercept, the expected demand value when the independent variable (X) is zero.

(b) is the slope of the regression line, which indicates the change in demand for each unit increase in (X) is the independent variable used to explain the changes in demand, which could include historical sales data or marketing expenditure.

Using this formula, analysts gather data on demand about one or more predictive variables. By applying statistical techniques, businesses can structure their forecasting models to estimate future demand based on current trends and historical data.

Integration with Microsoft Excel tools

Evaluations of demands that are still in the process of being fulfilled or have already been satisfied are called latent demand for needs.

Latent demand refers to potential demand that has not yet been expressed in actual purchases but may materialize if certain conditions are met, such as price changes, product availability, or marketing efforts. Low-latency analytics describes the capability to process and analyze data with minimal delay, enabling near real-time decision-making. In the context of retail, this means that sales and inventory data can be monitored and reacted to on a daily or even hourly basis. The market needs can only be forecasted without any strict indicators if they have not yet been expressed in demand, intentionally or unintentionally [6]. An example of the weekly Demand Calculation techniques of the Azerbaijan representative of the Danone company (Table 1).

Table 1

Calculation of Demand Forecast and order quantity based on historical data
(weekly short-term forecast for Danone Azerbaijan LLC)

1	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
2	Product name	W32	W33	W34	W35	W36	Average sales in pcs	Actual stock	Stock in Transit	Average daily sales	Needed for week	Coverage check for week	DOS coverage check	Demand Forecast	Safety stock days	Safety stock PCS	Order
3	CHEESE 170 STRAWBERRY	2673	2857	2830	2580	3056	2799	1281	3200	616	4312	169	0,3	**2799**	1	616	**3246**
4	CHEESE 170 PEACH	2032	2431	2542	2444	2890	2468	564	3200	543	3801	0	0,0	**2468**	1	543	**3011**
5	YOGHURT 150 NATURAL	3487	3480	3525	3521	3875	3578	2370	6360	788	5516	3214	4,1	**3578**	1	788	**1152**
6	YOGHURT 150 BANANA	5538	6672	5846	4804	5579	5688	3611	10800	1252	8764	5647	4,5	**5688**	1	1252	**1293**
7	YOGHURT 150 PRUNES	7899	11790	8964	6547	10795	9199	4215	15600	2024	14168	5647	2,8	**9199**	1	2024	**5576**
8	DRINK 270 PEACH	2160	2731	1247	1678	682	1700	1	0	340	3400	0	0,0	**1734**	2	680	**2414**
9	DRINK 270 NUTS	2226	2884	2522	2469	606	2141	1	0	429	4290	0	0,0	**2184**	2	858	**3042**
10	PRO BUTTER 180 82%	85	195	1407	144	342	435	0		87	609	0	0,0	**443**	1,5	130,5	**574**
11	PRO MILKUP 950 0,5%	630	772	0	759	938	620	13	0	124	868	0	0,0	**632**	10	1240	**1872**
12	PRO MILKUP 950 1,5%	1679	2943	0	4013	964	1920	612	0	384	2688	0	0,0	**1920**	10	3840	**5760**
13	PRO MILKUP 950 2,5%	2765	4016	0	3835	2616	2646	14	0	530	3710	0	0,0	**2699**	10	5300	**7999**
14	PRO MILKUP 950 3,2%	2054	5861	0	5491	3804	3442	54	0	689	4823	0	0,0	**3511**	10	6890	**10401**
15	TOTAL	33228	46632	28883	38285	36147	36635	12736	39160	7806	56949	14677		36855		24162	46340

Source: [Author 2020].

Explanation:

Average weekly sales (Column “G”): = Average of 5 weeks' sales data:

[\text{AVERAGE}(B3:F3)] (2)

Average daily sales (Column “J”): = Average of 5 weeks divided by 5 working days:

[\text{CEILING}\left(\frac{I4}{5} \cdot 1.1, 0\right)] (3)

Coverage check for 1 week (Column “L”): = If Actual stock (Column “H”) plus Stock in Transit (Column “I”) minus Needed stock for 1 week (Column “K”) is below zero, it means we cannot cover next week sale, If this formula above zero, we need to check how many days do we cover:

[\text{IF}(H2 + I2 - K2 < 0, 0, H2 + I2 - K2)] (4)

DOS (Days of Outstanding Sales) (Column “M”): = Coverage check for week (Column “L”) divided by Average daily sales (Column “J”)

[\frac{L2}{J2}] (5)

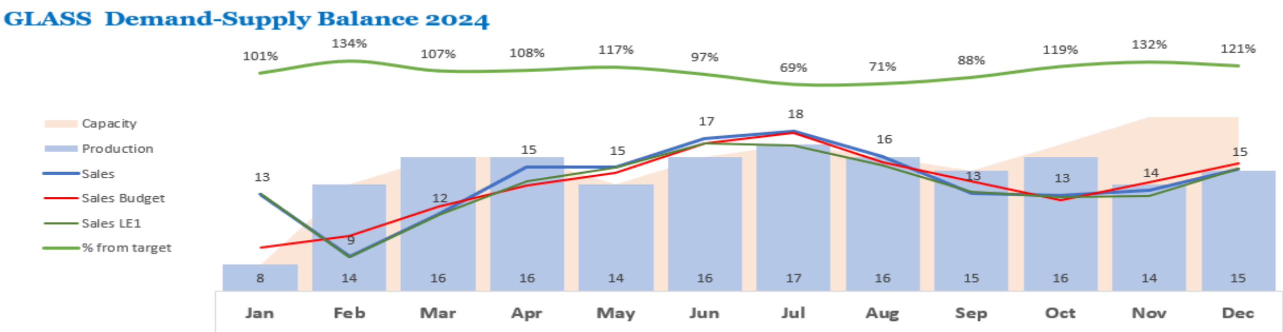
Demand Forecast calculation (Column “N”): = If Actual stock (Column “H”) is below Average daily sales (Column “J”), it means we don’t have yet stock even for 1 day sale so we need to get as the demand, average weekly sales quantity +20% (growing trend indicator) which is indicated in (Column “G”) if actual stock above 1 day sale we get as a demand 100% of average 5 week sales.

[\text{ROUND}\left(\text{IF}(H2 < J2, G2 \cdot 1.02, G2), 0\right)] (6)

Order quantity calculation (Column “Q”): = If the Demand forecast (Column “N”) plus Safety Stock (Column “P”) minus Coverage for week sale (Column “L”) is below zero, it measn no need for ordering any quantity, if above zero we ordering the quantity with calculating Demand forecast (Column “N”) plus Safety Stock (Column “P”) minus Coverage for week sale (Column “L”).

[\text{ROUND}\left(\text{IF}(N2 + P2 - L2 < 0, 0, N2 + P2 - L2), 0\right)] (7)

Data for this report were gathered from various business units to assess the demand-supply balance for glass products. Analysis was performed using Power BI and the JDA program, crucial for processing large datasets and improving decision-making, especially in predicting production capacity. Utilization remains high until October, with Glass 2 production slated to begin in November, primarily allocated to the Geo region. The stock target will be managed within one month, focusing on KZ and RU regions, with KZ production details pending confirmation (Figure 1).



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Azerbaijan	410%	134%	106%	60%	157%	108%	88%	272%	218%	100%	100%	100%
Baltics	198%	115%	39%	57%	25%	7%	41%	105%	165%	134%	107%	102%
Belarus	135%	82%	78%	110%	106%	68%	89%	123%	196%	115%	100%	100%
Georgia	119%	173%	148%	120%	102%	72%	73%	80%	111%	101%	100%	100%
Kazakhstan	162%	376%	149%	125%	130%	123%	95%	67%	83%	134%	171%	145%
Russia	93%	91%	91%	105%	115%	90%	50%	57%	74%	101%	101%	100%
Uzbekistan	142%	196%	132%	123%	97%	48%	54%	34%	92%	100%	100%	100%
Ukraine	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
M2O	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	98%

Figure 1. Last estimation of the Demand-Supply balance (Glass products) calculation report for “IDS Borjomi Georgia” LLC) [Author 2024]

Key Time Series Forecasting Techniques

Moving Average: [MA_t = \frac{1}{n} \sum_{i=0}^{n-1} Y_{t-i}] (8)

Explanation:

(MA_t) gives the moving average at time (t).

(n) is the number of past periods (for instance, months or weeks) used to calculate the average, which can smooth out short-term fluctuations.

(Y_{t-i}) represents the observed sales values at previous periods (from the most recent back to the (n^{th}) previous period).

The moving average helps identify underlying trends in sales data by filtering out random variations, thus providing a clearer view of demand patterns over time (Figure 2).

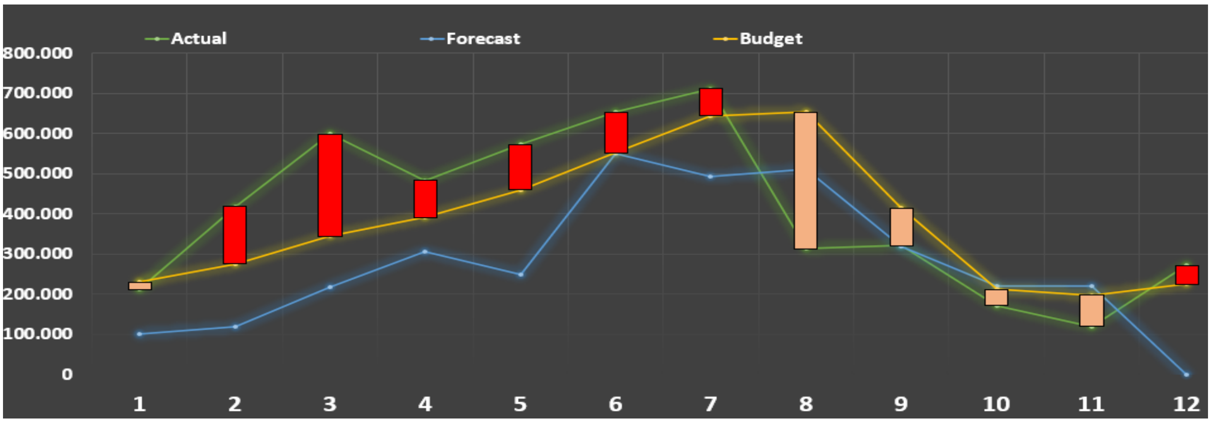


Figure 2. Annual 2023 forecast, demand and budget fluctuations diagram with demonstrating trends and seasonality of IDS Borjomi Azerbaijan. Source: [Author 2023]

Exponential Smoothing:

[S_t = \alpha Y_t + (1 - \alpha) S_{t-1}] (9)

Explanation:

(S_t) is the smoothed forecast value for the current period.

(Y_t) is the actual demand observed in the current period.

(S_{t-1}) is the forecasted value from the previous period.

The parameter (\alpha) (smoothing constant) determines how much weight is given to the most recent observation versus the previous forecast, with values between 0 and 1.

Machine Learning Algorithms Techniques

Machine learning algorithms significantly enhance demand forecasting and operational efficiency by analyzing patterns within historical datasets. These algorithms adjust and improve as more data becomes available.

Evaluation Metrics for Forecast Accuracy. Mean Absolute Error (MAE):

[MAE = \frac{1}{N} \sum_{t=1}^{N} |Y_t - \hat{Y}_t|] (10)

Explanation:

(Y_t) is the actual demand at time (t).

(\hat{Y}_t) is the forecasted demand at time (t).

(N) is the total number of forecasts evaluated.

MAE measures average forecasting errors, serving as a key metric for assessing accuracy and helping businesses reduce discrepancies between forecasted and actual demand [5].

Mean Absolute Percentage Error (MAPE):

[MAPE = \frac{100}{N} \sum_{t=1}^{N} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right|] (11)

Explanation:
Similar to MAE, but assesses the errors as a percentage of the actual demand.
MAPE allows organizations to understand forecast performance relative to the scale of actual sales, making it easier to compare accuracy across different products or market segments (Table 2).

Table 2

Calculation of Monthly Forecast Accuracy (MFA) for "IDS Borjomi Azerbaijan" LLC)
on an example of the Annual 2024 total

ANNUAL 2024	January	February	March	April	May	June	July	August	September	October	November	December	TOTAL
Forecast	128838	175590	310253	357219	381367	558237	642363	430945	327248	321768	258445	247896	**4140169**
Actual	110637	143891	253154	341292	379593	575217	638000	526826	325830	321542	343818	333815	**4293615**
Error	40122	59497	86361	116151	117320	70016	100496	166969	96143	71082	134323	107446	**1165926**
MFA	64%	59%	66%	66%	69%	88%	84%	68%	70%	78%	61%	68%	**75%**

Source [Author 2024]

Explanation:
Absolute value of a number (ABS) calculation:

[\text{ABS}({Actual} - {Forecast})] (12)

Forecast Accuracy (FA) calculation: If 100% minus "Error" is divided by Forecast below zero, then the value will be zero; otherwise, the value will be 100% minus "Error" divided by "Forecast".

[\text{IF}\left(1 - \frac{Error}{Forecast} < 0, 0, 1 - \frac{Error}{Forecast}\right)] (13)

This graph presents key insights into the forecasts and actual performance metrics for 2024. It highlights the relationship between expected and achieved results, along with error rates in the forecasts. Analyzing this data will enhance understanding of trends and inform decision-making processes (Figure 3).

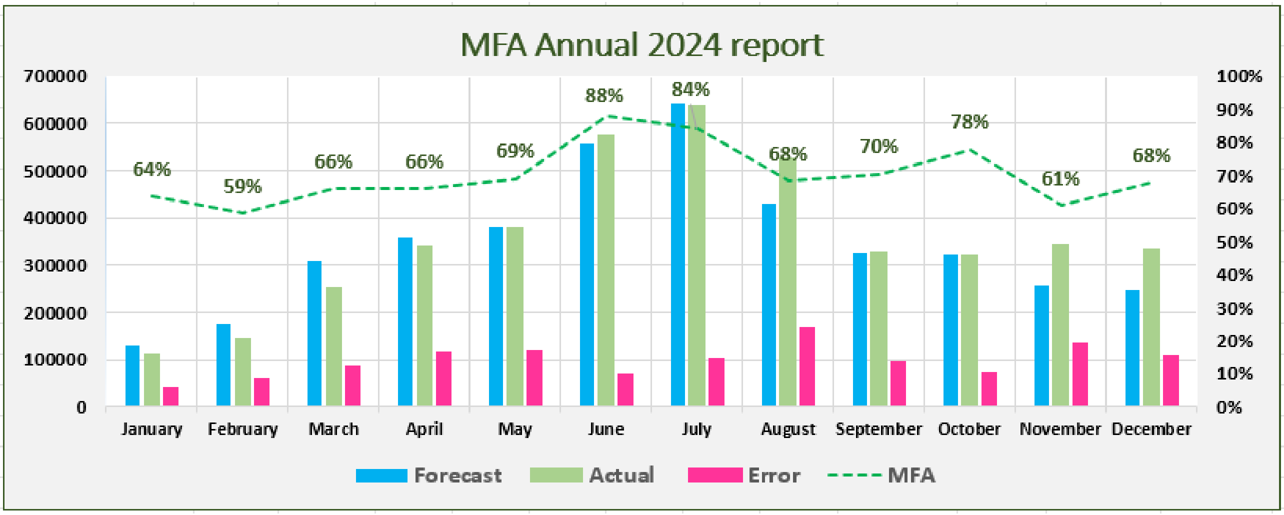


Figure 3. Visualisation of MFA report 2024. Source: [Author]

Calculation test

The graph demonstrates that the evaluation of demand planning and inventory calculation methodologies, as referenced in the article, was executed using the Power BI platform. This analysis is encapsulated under the section titled "Relevant Calculation Tests from the Power BI Tool," highlighting the effectiveness and precision of the calculations performed (Figure 4).

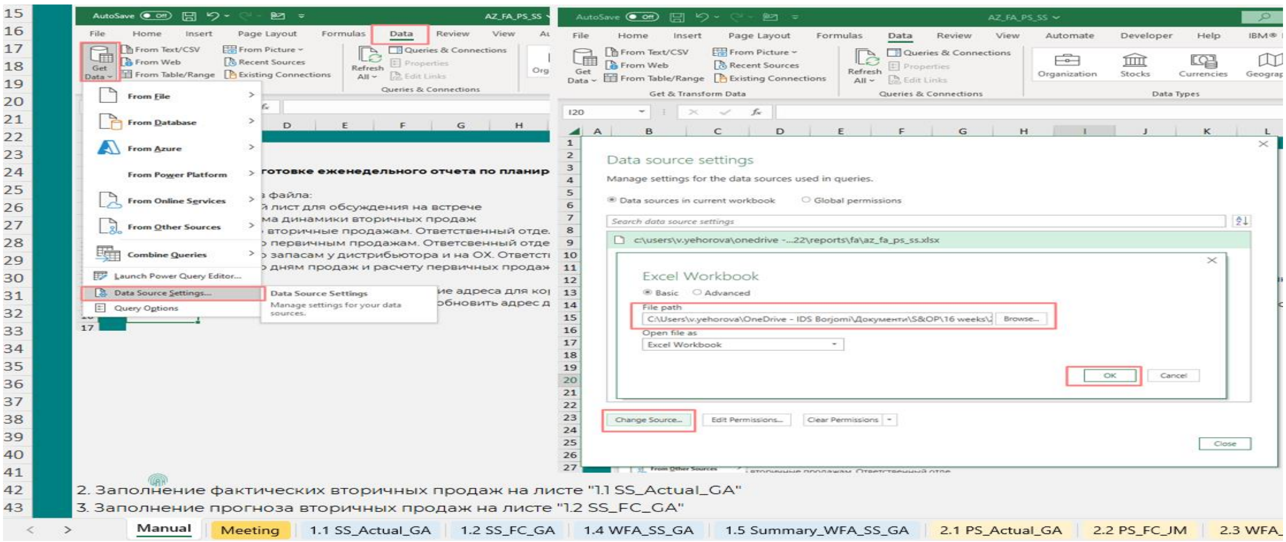


Figure 4. Relevant calculation tests from the Power BI tool. Source: [Author]

Comparative analysis Global VS Azerbaijan

To systematically understand the current activities of Azerbaijani companies in the application of inventory management strategies and approaches, 26 interviews were conducted both in local large companies in various sectors such as retail, energy, pharmaceuticals, manufacturing.

The interviews involved professionals from 20 companies of various positions in the supply chain area (Figure 5).

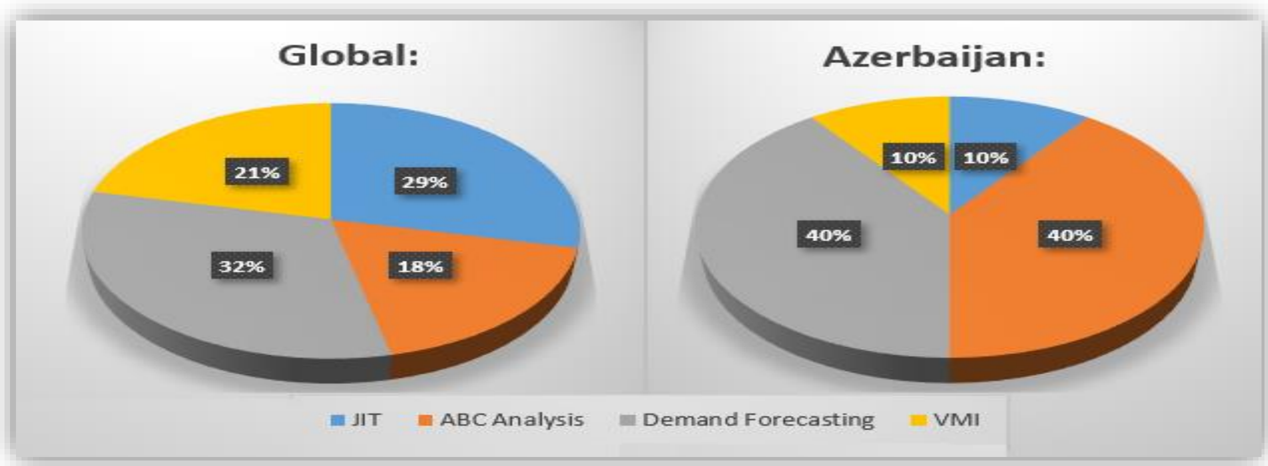


Figure 5. Pie chart of Global VS Azebaijan IM key Aspects by %
Source: Created by (Author) based on www.netstock.com (Netstock Research)

Conclusion

This study highlights the profound impact of Big Data analytics on enhancing demand forecasting accuracy in Azerbaijan's retail market. Among the methodologies analyzed, machine learning algorithms stand out as the most effective for addressing demand planning challenges. These advanced techniques enable real-time data analysis and pattern recognition, resulting in more precise forecasts than traditional methods like Simple Linear Regression and Exponential Smoothing.

Companies such as Danone and IDS Borjomi Georgia exemplify the successful use of these methodologies, employing tools like Power BI and advanced Microsoft Excel functions to optimize inventory management and reduce costs. Their integration of data-driven techniques illustrates how organizations can align supply chains more effectively with changing consumer demands.

Moreover, collaboration among industry leaders enhances knowledge sharing, fostering improved forecasting practices that can address the unique challenges in Azerbaijan's market. Future research should explore the ongoing evolution of these methodologies and how further advancements in collaborative data practices can strengthen the role of Big Data analytics in demand planning, ensuring business competitiveness in a dynamic economic landscape.

REFERENCES

1. Huseynov A.S., & Hesenova I.M. The role of enterprise resource planning ERP systems in the supply chain. UNEC, Scientific works, 1996, pp. 137–142. https://doi.org/10.58225/tim. 2024-2-137-142
2. He L. (n.d.). Multi-Echelon Inventory Optimization and Demand-Side Management: Models and Algorithms. pp. 50-62. http://preserve.lehigh.edu/etd?utm_source=preserve.lehigh.edu%2Fetd%2F1504&utm_medium=PDF&utm_campaign=PDFCoverPages
3. Lei Y., Qiaoming H., & Tong Z. Research on Supply Chain Financial Risk Prevention Based on Machine Learning. Computational Intelligence and Neuroscience, 2023(1), 6531154. pp. 5-14. https://doi.org/10.1155/2023/6531154
4. Nozari H., Szmelter-Jarosz A., & Ghahremani-Nahr J. Analysis of the Challenges of Artificial Intelligence of Things (AIoT) for the Smart Supply Chain (Case Study: FMCG Industries). Sensors, 22(8), 2931, 2022, pp. 3-5. https://doi.org/10.3390/s22082931
5. Petropoulos F., Grushka-Cockayne Y., Siemsen E., & Spiliotis E. Wielding Occam's razor: Fast and frugal retail forecasting (No. arXiv:2102.13209). 2023. pp. 4-14. https://doi.org/10.48550/arXiv.2102.13209
6. Schnegg M., & Möller K. Strategies for data analytics projects in business performance forecasting: A field study. Journal of Management Control. 33(2), 2022, pp. 241–271. https://doi.org/10.1007/s00187-022-00338-7
7. Shenhao L. (n.d.). Walmart's Data Analytics for Optimised Inventory and Customer Insights. pp.2-4. https://www.researchgate.net/publication/377272036_ARTICLE_TITLE_Walmart%27s_Data_Analytics_for_Optimised_Inventory_and_Customer_Insights
8. Taghizadeh E. (n.d.). Utilizing Artificial Neural Networks To Predict Demand For Weather-Sensitive Products At Retail Stores. pp. 3-7. https://www.researchgate.net/publication/321241806_Utilizing_artificial_neural_networks_to_predict_demand_for_weather-sensitive_products_at_retail_stores
9. Vandeput N. Inventory Optimization: Models and Simulations. De Gruyter. 2020, pp. 18-24 https://doi.org/10.1515/9783110673944
10. Žunić E., Korjenić K., Delalić S., & Šubara Z. Comparison Analysis of Facebook's Prophet, Amazon's DeepAR+ and CNN-QR Algorithms for Successful Real-World Sales Forecasting. International Journal of Computer Science and Information Technology, 13(2), 2021, pp. 67–84. https://doi.org/10.5121/ijcsit.2021.13205

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