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DYNAMIC ABC ANALYSIS FOR ASSORTMENT MANAGEMENT IN 3PL

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Purpose: The purpose of this article is to present the impact of the developed dynamic ABC tool on inventory management within the operations of a third-party logistics (3PL) company.
Design/methodology/approach: The research focused on designing the dynamic ABC tool and subsequently using it in a case study involving 52 customers for whom a 3PL logistics operator provides services. The customers were grouped into categories such as food, nonfood, pharma, and other, and the study encompassed 10 physical depots located in Poland and the Czech Republic.
Findings: The implementation of the dynamic ABC tool will influence the inventory management of the 3PL company. Furthermore, the dynamic ABC tool performs similarly under various conditions for different types of customers, which could indicate its attributes related to universality of application.
Research limitations/implications: The main limitations of the study are the p-value results from the conducted correlation analysis, suggesting that alternative tests should be considered for correlations. Additionally, the conducted quantitative studies should, in the author's opinion, be complemented by a thorough qualitative analysis of the described phenomena.
Originality/value: The presented results provide a significant contribution to understanding the impact of a dynamic SKU classification approach on inventory management in the context of a logistics operator. Through literature analysis, it can be observed that traditional ABC methods primarily rely on historical data, limiting their flexibility. In this context, dynamic ABC analysis, combining classification with predictive data analysis, could serve as a valuable tool for enhancing inventory management efficiency.

Keywords: 3PL, logistic operator, ABC analysis, inventory management.

Category of the paper: Research paper.

1. Introduction

The contemporary economic world presents numerous challenges to logistics operators, linked to increasingly complex supply networks (Datta et al., 2013; Maas et al., 2018), dynamic market changes (Arun, Yildirim Ozmutlu, 2022), and growing competition (Vivaldini et al., 2008). Effective goods distribution has become a crucial factor for the success of many companies, and logistics operators play an incredibly significant role in ensuring its smooth operation. To meet these challenges, logistics operators must make strategic decisions that have a crucial impact on inventory management, costs, and customer satisfaction. Efficiency and effectiveness in managing warehouses, deliveries, and goods flow are key elements in achieving competitive advantage (Baruffaldi et al., 2020). In this context, ABC analysis stands out as a powerful tool to support decision-making processes. Often referred to as Pareto analysis or the 80/20 principle (Rusanescu, 2014), it is based on dividing elements of a set according to their significance or impact on a given phenomenon. Through ABC analysis, logistics operators can focus their efforts on key products that have the greatest impact on business outcomes, as well as on customers who constitute a significant portion of turnover. This method classifies set elements into three categories: A, B, and C. Class A elements are those with the greatest impact on outcomes, typically representing about 20% of the whole set, but accounting for 80% of value or turnover. Class B elements are moderately significant, while Class C elements have the smallest impact on outcomes but constitute a large portion of the set.

ABC analysis allows logistics operators to understand which products, customers, or suppliers are crucial for achieving business goals (Abbas Shojaie et al., 2016; Beheshti et al., 2020). This enables them to more precisely direct their actions, concentrating their resources and efforts on the most important areas of operation. The result is optimized inventory management, avoidance of unnecessary costs, and better fulfillment of customer needs and expectations. ABC analysis becomes an invaluable tool for logistics operators, enabling higher efficiency, competitiveness, and increased satisfaction for both customers and the company itself. With the support of this method, logistics operators can make more rational and informed decisions that will yield positive results in their operations. However, the ABC method has several limitations, which are mitigated by various extensions and modifications (notably observed in Abdolazimi et al., 2021b and Millstein et al., 2014). One of these limitations, focused on in this article, is the fact that the ABC method relies on historical data, thus solely on information related to what has already happened. Even the XYZ method, which supports ABC through an additional dimension, still relies on historical data for analysis. To address this issue, the author suggests introducing a tool for dynamic ABC analysis, which would also incorporate information provided by predictive tools used by 3PL operators to forecast future demand. The aim of the article is to present the functioning of this tool based on a conducted case study. The article attempts to verify the hypotheses:

- H1: Dynamic ABC analysis will impact SKU allocation in 3PL warehouses, influencing inventory management.
- H2: Regrouping in ABC caused by the application of dynamic ABC will exhibit correlations within physical depots and product groups.

These hypotheses will be verified based on literature analysis and the results of the conducted case study. The presented article provide a significant contribution to understanding the impact of a dynamic SKU classification approach on inventory management in the context of a logistics operator. Through literature analysis, it can be observed that traditional ABC methods primarily rely on historical data, limiting their flexibility. In this context, dynamic ABC analysis, combining classification with predictive data analysis, could serve as a valuable tool for enhancing inventory management efficiency.

2. Theoretical background

2.1. 3PL in the contemporary market

The logistics industry has undergone a significant transformation thanks to technological advancements. Third-party logistics (3PL) companies specialize in providing integrated logistics services, such as transportation, warehousing, inventory management, packaging, and information management, to facilitate the movement of goods from suppliers to customers (Mangan, Lalwani, 2016). These companies act as intermediaries between shippers and carriers, offering value-added services like order fulfillment, consolidation, customs clearance, and reverse logistics to improve supply chain performance (Ajakaive, 2012). 3PLs offer a comprehensive suite of logistics services tailored to meet the specific needs of each customer, including transportation, warehousing, distribution, inventory control, order processing, and information management (Griffis et al., 2007). They optimize the flow of goods and information across the supply chain through services like freight forwarding, customs brokerage, transportation management, and value-added activities (Herold et al., 2021).

By embracing digital technologies, data analysis, and data-driven insights, 3PLs can streamline their processes and provide value-added solutions to clients. Digitalization allows for automation of manual tasks like order processing, inventory management, and shipment tracking. Advanced software systems and technologies improve the accuracy and speed of operations, leading to enhanced efficiency and cost savings. Automation also reduces the risk of human errors, enabling 3PLs to focus on strategic activities that require human expertise.

3PLs are essential players in the global supply chain, offering logistics services to businesses across various sectors (Huge-Brodin et al., 2020). Their services cover transportation, warehousing, inventory management, order fulfillment, and other value-added activities. They act as intermediaries between manufacturers, suppliers, retailers, and end consumers, ensuring a smooth flow of goods and information. The adoption of technology, including digitization of information and the use of advanced software systems, has improved visibility and transparency across the supply chain. Data analytics and predictive modeling empower 3PLs to make data-driven decisions, optimize routes, and streamline operations, leading to cost savings and improved service levels (Sanchez-Rodrigues, Kumar, 2019). E-commerce and increasing consumer expectations for fast deliveries have driven innovation in last-mile logistics, with 3PLs using route optimization algorithms, mobile apps, and real-time tracking systems to enhance delivery efficiency and provide accurate updates to customers. Moreover, emerging technologies like the Internet of Things (IoT), blockchain, and artificial intelligence (AI) have found adoption in the logistics industry, offering opportunities for improved supply chain visibility, enhanced security and traceability, and automation of various logistics processes. Overall, technology has played a crucial role in reshaping the logistics industry, with 3PLs embracing digital transformation to optimize operations, improve customer service, and stay competitive in the global supply chain (Sashi, 2023). By leveraging advanced technologies and data-driven insights, 3PLs can navigate logistics complexities more efficiently and effectively.

2.2. ABC analysis

The ABC method, in relation to inventory classification, is a well-known and widely practiced inventory management technique (Kampf et al., 2016; Pawar, Landage, 2023). Its application can lead to cost reduction and increased operational efficiency for a company (Kiyak et al., 2015). The ABC method also finds application in other fields of knowledge; it can be used for classifying suppliers, projects, and other elements (Rusanescu, 2014). In business practice, the ABC method is often applied to categorize raw materials used in manufacturing processes (Pandya, Thakkar, 2016). However, it's worth noting that this method is not limited solely to raw materials and can be used across various product and service groups. Implementing ABC allows for effective inventory management, increased management efficiency, and improved profit margins (Liu, Wu, 2014). The main steps in the traditional application of the ABC method include (Indrasan et al., 2018):

Step 1: Determine the unit cost and usage of each material over a specified period.

Step 2: Multiply the unit cost by the estimated annual usage to obtain the net value.

Step 3: Create a list of all items and arrange them in descending order of value (annual value).

Step 4: Accumulate values and sum the number of items, then calculate the percentage contribution to the total inventory value and item count.

Step 5: Plot a graph of percentage of items and value.

Step 6: Mark appropriate boundaries for the A, B, and C categories on the graph.

If the ABC method is not implemented correctly, it can lead to serious problems and incidents in inventory management (Dhoka and Choudary, 2013). As some authors suggest, the use of ABC can also be part of the design of supply chains (Abdolazimi et al., 2021a). The traditional ABC method is straightforward to implement, but some researchers have gone further by exploring potential extensions of this method to create more flexible groups that can even accommodate complex business scenarios. An overview of the most popular ABC extensions is presented in Table 1.

Table 1.
Traditional ABC modification propositions

Traditional ABC modification proposition	Research papers
ABC grouping supported by Analytic Hierarchy Process (AHP) method.	(Partovi, Burton, 1993)
ABC assortment grouping using multiple criteria	(Ng, 2007; Hadi-Vencheh, 2010; Flores, Whybark, 1987; Ramanathan, 2006; Zhou, Fan, 2007; Yu, 2011; Li et al., 2019)
ABC supported by weighted linear optimization and other optimization methods.	(Ramanathan, 2006; Zhou, Fan, 2007; Millstein et al., 2014)
ABC supported by artificial intelligence methods for classification.	(Yu, 2011)
ABC supported by artificial neural networks (ANN) and cluster classification	(Saric et al., 2014)
Multicriteria ABC inventory classification using acceptability analysis	(Li et al., 2019)
ABC supported by advanced mathematical models.	(Abdolazimi et al., 2021b)
Mixing the qualitative and quantative methods for ABC calculation.	(Torabi et al., 2012)
ABC grouping based on distance optimization in the internal logistics.	(Bhattacharya et al., 2007)
ABC supported by fuzzy classification methods.	(Chu et al., 2008, Chawla et al., 2024; Khan, Khan, 2023)

Source: own elaboration.

As evident in Table 1, one of the most frequently addressed topics in modifying the traditional ABC approach is enhancing ABC classification with multi-criteria analysis. In the literature, numerous models utilize multi-criteria analysis in conjunction with ABC, such as the PROAFTN model presented by Douissa and Jabeur (2016) or the GAMIC model (Guvenir, Erel, 1998; Ravinder, Misra, 2014). However, ABC is more commonly recognized and employed as a component of models for determining order quantity (Nallusamy et al., 2017). The classification itself is often used as a complement to ordering methods based on economic order quantity (EOQ), as seen in Kachitvichyanukul et al. (2012) and Vanesa and Helma (2023), or for inventory control, particularly when combined with the MIN-MAX method (Asana et al., 2020).

In practical business applications, ABC is most commonly used in conjunction with the XYZ method (Suryaputri et al., 2022; Pandya, Thakkar, 2016; Dhoka, Choudary, 2013). Common approaches to XYZ analysis include determining the coefficient of variation (CV) value (Suryaputri et al., 2022) or utilizing ex-post errors (Al.-Dulaime, Emar, 2020). The CV is calculated using the following formula (Brown, 1998):

$$\mathrm{CV} = \frac{\mathrm{S}}{\bar{\mathrm{x}}}, \tag{1}$$

where:
S – standard deviation,
$\bar{x}$ – average value.

CV describes the degree of data variability; therefore, in the context of inventory management, it provides information about the variability of demand for a particular product. In the literature, attempts have been made to categorize XYZ groups based on CV values.

One of the classifications, proposed by Kaczorowska et al. (2019), has been presented in Table 2.

Table 2.
XYZ classification based on CV indicator

Group	CV value
X	<0; 0,5>
Y	(0,5; 0,9>
Z	(0,9; ∞)

Source: own elaboration.

Certainly, it's important to be aware that when determining CV values, the ranges should be established based on a good understanding of the assortment being managed in inventory management. Various factors influence these groups, and rigid categorization may not be suitable in this context. For example, SKU (Stock Keeping Units) on the warehouse shelves in the FMCG (Fast Moving Consumer Goods) industry will be structured differently compared to industries where rotation and frequency of issues don't reach such levels (e.g., construction industry). Another mentioned method of classification involves categorization using ex-post errors generated for individual SKUs. If forecasts are created within inventory management, the errors and forecasting accuracy can be used for XYZ classification. Ex-post errors in forecasting vary, but the most commonly mentioned ones (including in Satchell and Hwang (2001) and Ostertagova and Ostertag (2012)) for XYZ analysis and inventory management are MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), and RMSE (Root Mean Square Error). Table 3 compiles these mentioned errors along with explanations of how they are calculated.

Table 3.
The most popular ex-post errors in the case of XYZ analysis

Forecasting error	Equation	Description
MAE	$\frac{1}{n}\sum_{i=1}^{n}\lvert y_i - y_i^*\rvert$	
MAPE	$\frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{y_i - y_i^*}{y_i}\right\rvert$	y_i – real value in i-period. $y_i^{\wedge}$ – forecast value in i-period. n – number of observations.
RMSE	$\sqrt{\sum_{i=1}^{n}\frac{(y_i - y_i^{\wedge})^2}{n}}$	

In the case of XYZ classification, selecting appropriate values that suggest an SKU is placed in the right class is also an individual matter. Despite certain authors providing guidelines (such as Herlamband and Parung (2021)), who suggest the following classes for specific MAPE error ranges: X for results less than 35%, Y for results less than 60%, and Z for the rest, the treatment of forecast errors as small or large depends on many factors related to business strategy, SKU type, and the operational environment of the company. However, advanced forecasting systems nowadays offer the possibility of minimizing errors and increasing forecast accuracy.

3. Methods

3.1. Dynamic ABC idea

As mentioned earlier, a commonly recognized drawback of ABC is its reliance on historical data, often conflicting with its flexibility. Apart from the advanced modification methods discussed earlier in the literature, the potential of prediction in inventory management is also emerging. Some authors emphasize that predictive capabilities can lead to a decrease in the total number of parts inventoried monthly, resulting in greater storage space availability and lower stock holding costs (Ternero et al., 2023). On the other hand, some authors clearly showcase ABC models supported by value estimation (Chen, 2011). Certain authors see an opportunity to support classical ABC with forecasting (Sharma, Tripathi, 2023; Quiroz-Flores et al., 2023) or suggest combining ABC with a forecasting module in MPS (Master Production Schedule) to minimize production costs (Simanjuntak et al., 2022). Meanwhile, Muenjitnoy et al. (2023) suggested that their research results could be applied to the ABC analysis technique to select inventory and then forecast demand for the most accurate inventory estimate based on MAPE. It is on these foundations that the concept of dynamic ABC emerged, as presented in the article. Dynamic ABC is based on combining ABC classification with predictive data analysis in the decision-making and relocation processes. The operational idea of a SKU classification tool based on dynamic ABC is depicted in Figure 1 using BPMN 2.0 (Business Process Modeling and Notation 2.0).

The research was conducted in the form of a case study within the operations of a selected third-party logistics (3PL) operator that operates in multiple distribution networks. The chosen 3PL company is an international logistics firm specializing in supply chain services. They provide solutions in procurement, warehousing, distribution, transportation, and supply chain management. The company's activities span across various industries, such as food, industrial products, electronics, and many other goods. Their services are offered both in the domestic and international markets. Equipped with advanced technologies and IT systems, the company can track shipments, manage inventory, and optimize logistics processes. Their focus is on delivering high-quality customer service by adapting flexibly to customer needs and swiftly responding to changing market requirements. Sustainability is also a key aspect of their operation, aiming to minimize their impact on the environment. The company holds a strong position in the logistics market, continually expanding and enhancing its competencies on a global scale.

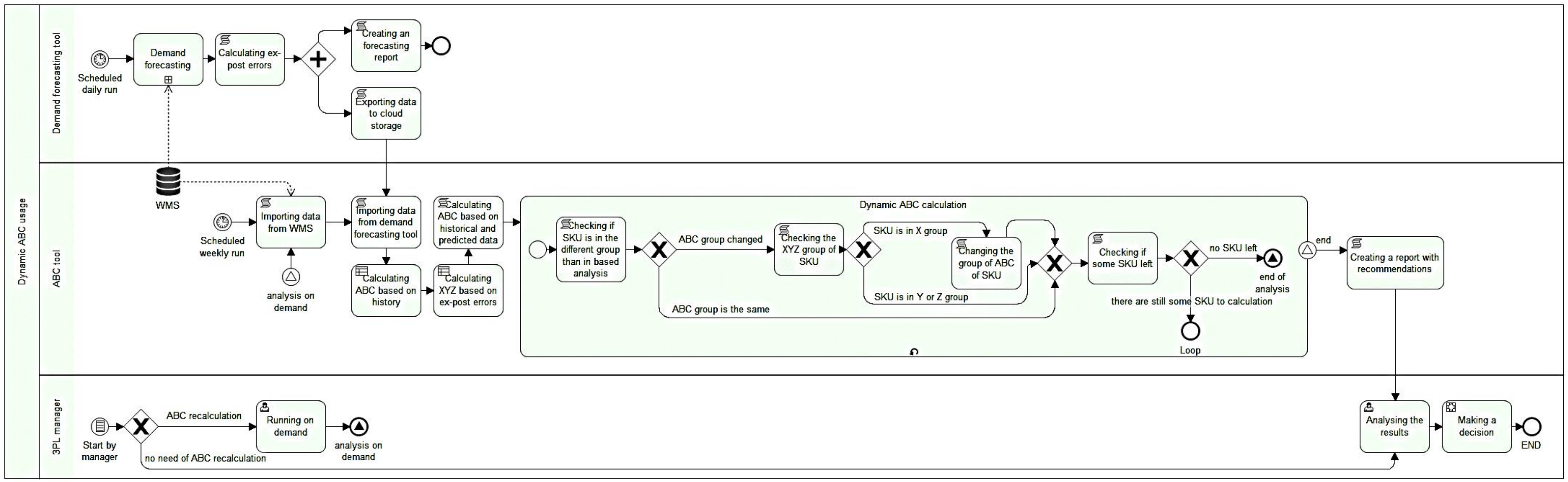

Figure 1. Process of dynamic ABC tool usage mapped in BPMN 2.0 (for better quality check the: https://tiny.pl/crpdv).

Source: own elaboration.

The tool developed by the author requires the utilization of a forecasting tool, which provides information about forecasts and the verifiability of expired forecasts. Such a forecasting tool, applicable in such scenarios, is presented in the work by Kmiecik and Wolny (2022). The values for XYZ classification of SKUs were determined individually, depending on the specifics of each service recipient's operations. Based on the XYZ analysis, the tool decides whether to change the ABC group calculated based on historical data to the group calculated based on predictive data. This change occurs only when the SKU is in group X, and the ABC calculation using predictive data indicates a change. The stringent rules for changing the group are linked to the need for obtaining high-quality information (information with a high probability of accuracy) to justify the reorganization of products in the warehouse, including the allocation of resources for SKU relocation.

3.2. Data description

To construct the case study, data collected from 10 warehouses located in Poland (7 warehouses) and the Czech Republic (3 warehouses) were utilized. The total number of service recipients examined within the scope of logistic services outsourcing by the 3PL in these mentioned warehouses amounts to 52 service recipients. An overview of the recipients is available in Table 4 (Appendix 1). The examined service recipients were classified into groups representing industries such as food, non-food, pharmaceutical (pharma), and others. The number of service recipients in each warehouse is presented in Table 5.

Table 5.
Number of service recipients in the particular warehouses

Warehouse	Number of customers	Number of SKU	food	nonfood	pharma	other
Physical depot 01 PL	1	160 862	0	1	0	0
Physical depot 02 PL	3	48 330	3	0	0	0
Physical depot 03 PL	31	105 448	0	5	25	1
Physical depot 04 PL	3	13 419	3	0	0	0
Physical depot 05 PL	3	17 235	1	2	0	0
Physical depot 06 PL	2	34 662	0	2	0	0
Physical depot 07 PL	1	7 644	1	0	0	0
Physical depot 08 CZ	5	375 265	2	2	0	1
Physical depot 09 CZ	2	144 225	1	1	0	0
Physical depot 10 CZ	1	13 467	0	1	0	0
TOTAL	**52**	**920 557**	**11**	**14**	**25**	**2**

Source: own elaboration.

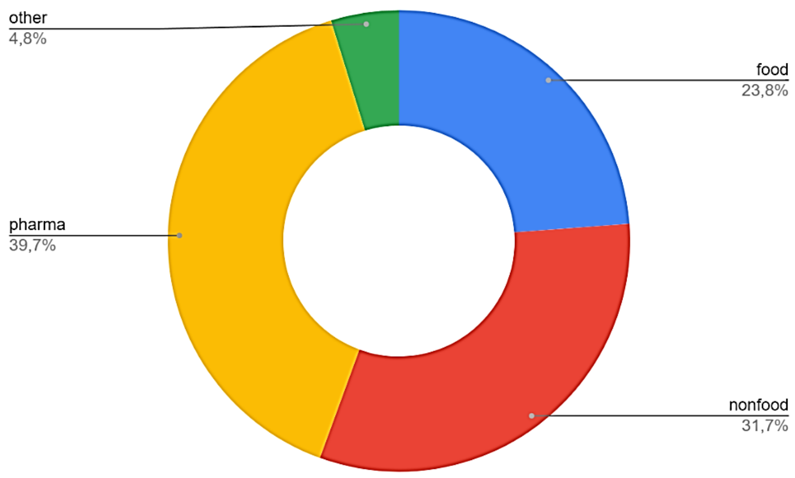

Figure 2. Types of service recipients in the case study.

Source: own elaboration.

Approximately 40% of the examined recipients are recipients of logistic services, involving handling products from the pharmaceutical industry. However, the significant presence of food (around 23%) and non-food (around 32%) enterprises will diversify the results of the conducted case study, thus ensuring a satisfactory level of research universality. The data pertains to the classification performed by the presented tool for around 920,000 SKUs that exhibit movement (dead SKUs were excluded from the study) across the 10 warehouses located in two countries. The analysis verified the last 3 months for ABC group calculation and the last 6 months for forecast verifiability calculation. The forecast horizon, which was used to change the group within the ABC group, was determined individually for each service recipient and ranged from 1 week to 1 month.

3.3. Main research steps

The research procedure focuses on completing several predefined research steps (Figure 3).

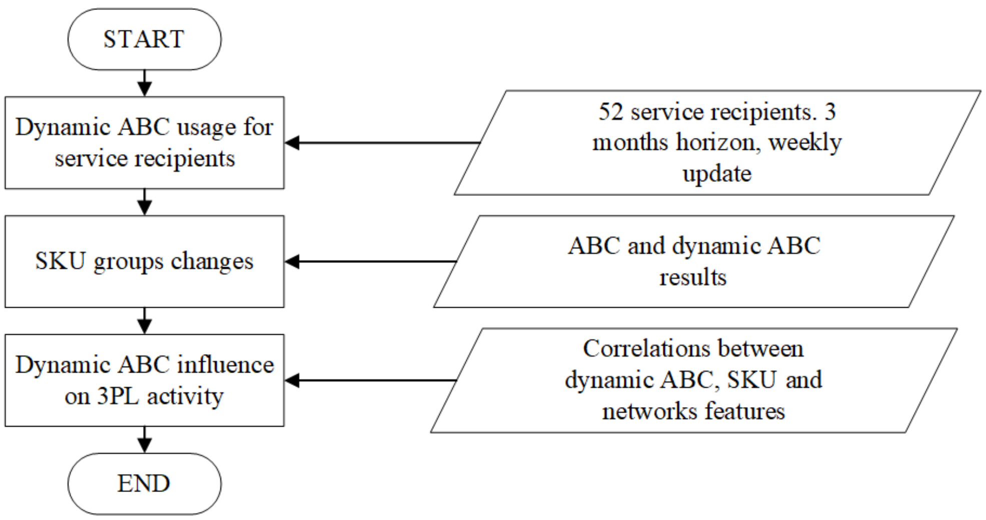

Figure 3. Main research steps.

The research is focused on 52 service recipients for whom the dynamic ABC tool was utilized (Figure 1). The period of tool application for each of the service recipients was 3 months, covering standard operational months for the operator, without exceptional sales peaks, promotional activities, or holiday periods. The choice of this period aimed to standardize the research. The dynamic ABC tool was executed once a week. Daily execution of the tool would not be efficient due to the constant need for product relocation in the storage area, which would consume resources and time without compensating for the benefits of using the tool. The tool was activated weekly, allowing for a potential change of SKUs between groups during the mentioned 3-month period to occur 12 times. The decision to use the tool on a weekly basis was a strategic decision made by the managerial level of the operator. This way, the average percentage of SKUs that switched to another group with each tool activation was calculated. Group changes mainly occurred between the extreme SKUs that were located at the border of groups A and B, as well as B and C. In the final step, a correlation analysis was conducted between the outcomes of ABC group changes influenced by the tool's operation, the specifics of the service recipient's activity, and the number of SKUs present for each service recipient. R software was employed for the correlation analysis, using three widely used methods for calculating correlations: Pearson correlation, Spearman rank correlation, and Kendall's tau correlation (Chok, 2010). The calculation method for these correlations is presented in Table 6.

Table 6.
Chosen correlation coefficients

Correlation	General equation	Assumed values interpretation	Part of R script
Pearson	$r = \frac{n\sum XY - \sum X \sum Y}{\sqrt{(n\sum X^2 - (\sum X)^2 - (n\sum Y^2 - (\sum Y)^2)}}$ where: n – number of data points, X – x-values in the data set, Y – y-values in the data set.	|r| = 0 – no correlation. |r| = 1 – perfectly correlation. |r| ∈ (0;0,3] - negligible correlation. |r| ∈ [0,3;0,5] – moderate correlation. |r| ∈ (0,5;1) – highly correlated.	*cor.test(X, Y, method = c(“pearson”))*
Spearman	$p = \frac{6\sum d_i^2}{n(n^2-1)}$ where: d – difference between ranks.	|p| = 0 – no correlation. |p| = 1 – perfectly correlation. |p| ∈ (0;0,3] - negligible correlation. |p| ∈ [0,3;0,5] – moderate correlation. |p| ∈ (0,5;1) – highly correlated.	*cor.test(X, Y, method = c(“spearman”))*

Cont. table 6.

Kendall	$$k = \frac{C - D}{C + D}$$ where: C – the number of concordant pairs, D – the number of discordant pairs.	|k| = 0 – no correlation. |k| = 1 – perfectly correlation. |k| ∈ (0;0,3] - negligible correlation. |k| ∈ [0,3;0,5] – moderate correlation. |k| ∈ (0,5;1) – highly correlated.	*cor.test(X, Y, method = c("kendall"))*

Source: own elaborated based on Cohen et al. (2009), De Winter et al. (2016), Abdi (2007) and www.RDocumentation.org

The analysis was conducted by examining correlations using the Pearson linear correlation coefficient, Spearman's rank correlation, and Kendall's tau correlation between the specified factors, with a statistical significance level set for results with a p-value < 0.05. Adopting a p-value of this level is common in scientific articles (Genovese et al., 2006; Goodman, 2008). In statistics, the p-value is a measure that determines the statistical significance of test results (Andrade, 2019). When calculating correlations, the p-value indicates whether the detected correlation between variables is statistically significant or could be a result of chance. A p-value < 0.05 means that there is less than a 5% chance that the observed correlation was obtained randomly in the sample. In other words, if the p-value is less than 0.05, the result can be considered statistically significant, suggesting a genuine relationship between the variables being studied. If the p-value is greater than or equal to 0.05, it means there is not enough evidence to reject the null hypothesis, which states that there is no correlation between variables. This does not automatically mean that there is no correlation, but it suggests that we do not have enough certainty to conclude that one exists.

4. Results

In the research conducted using the created tool, it was demonstrated that in the case of each service recipient, the tool influences the reassignment of SKUs among the different ABC groups (Figure 4).

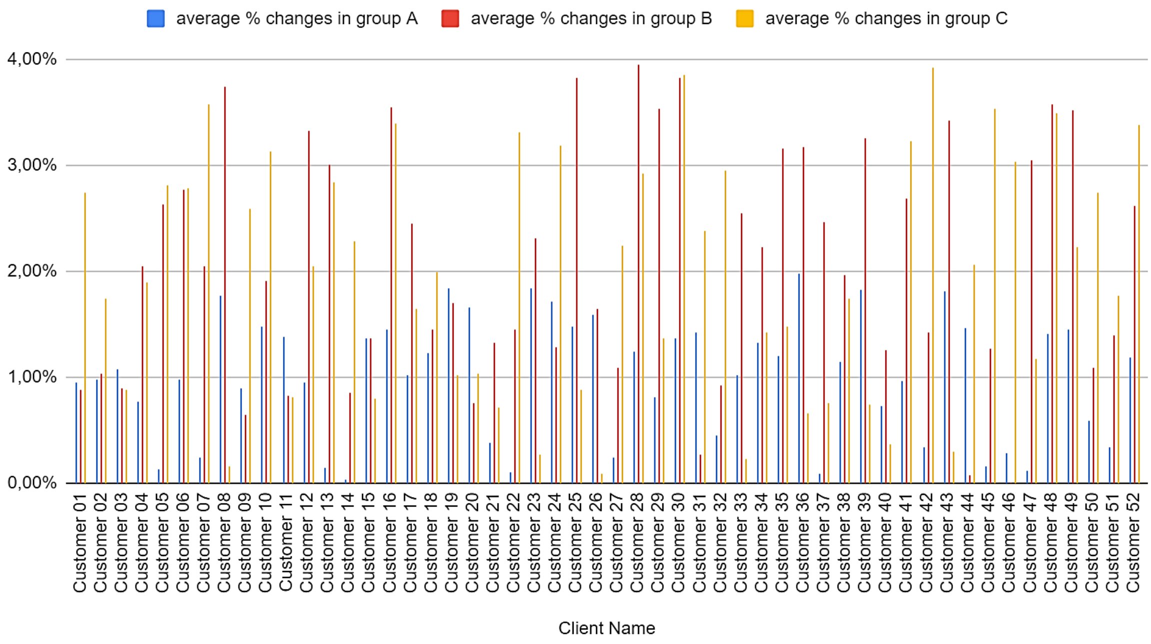

Figure 4. Average percentage changes in ABC groups per service recipients.

The relocation of the number of SKUs among different product groups was a significant aspect of the analysis, with an average level of change not exceeding 4% (differences ranged from 0.08% to 3.95% depending on the specific group). When considering the overall number of SKUs, which was an impressive 920,557, managed by a dedicated logistics operator as part of their services for customers, it becomes evident that the global modifications in warehouse management yielded scalable results. In practical terms, this means that an average transfer of 736 to as many as 36,362 SKUs took place across Poland and the Czech Republic, signaling substantial changes in warehouse space organization and logistics process optimization. These balanced relocations have the potential to contribute to more efficient resource utilization, optimized inventory management, and improved product availability for end customers. The average percentage of SKU movement within specific ABC groups was also analyzed for individual physical depots (table 7) and different types of service recipients (table 8).

Table 7.
Average percentage changes in ABC groups in the particular physical depots

Physical depot	average % changes in group		
	A	B	C
Physical depot 01 PL	0,96%	0,88%	2,74%
Physical depot 02 PL	0,94%	1,32%	1,51%
Physical depot 03 PL	1,06%	2,14%	1,94%
Physical depot 04 PL	1,07%	2,53%	1,05%
Physical depot 05 PL	1,18%	2,40%	1,44%
Physical depot 06 PL	1,08%	2,42%	2,11%
Physical depot 07 PL	1,46%	0,07%	2,07%
Physical depot 08 CZ	0,69%	2,29%	2,69%
Physical depot 09 CZ	0,47%	1,24%	2,26%
Physical depot 10 CZ	1,18%	2,62%	3,38%

Source: own elaboration.

Table 8.
Average percentage changes in ABC groups in the particular service recipients types

Service recipient type	average % changes in group		
	A	B	C
food	1,08%	2,05%	1,95%
nonfood	0,88%	1,98%	2,14%
pharma	1,07%	2,23%	1,82%
other	0,80%	0,77%	2,96%

Source: own elaboration.

Analyzing the movements between different ABC product groups within each physical depot, it was observed that SKU relocations between these groups occurred in all three categories (A, B, and C). The percentage values of these movements varied, with the highest number of changes observed in group C, accounting for approximately 2.12% of all SKUs. On the other hand, group A exhibited a lower level of movements, around 1.01%. Group B, meanwhile, encompassed about 1.79% of SKUs that were transferred between the different product groups. When examining the data from the perspective of different types of service recipients, a similar tendency towards even SKU movements across different recipient categories was noted. For the "food" category, an average of 1.69% of all SKUs were relocated, while for "non-food," it was 1.67%, "pharma" showed 1.71%, and other types of recipients had 1.51%. Incidentally, the structure of changes in the ABC groups reflected similar patterns to those in the physical depots. Focusing on movements within these groups, analogous trends were observed. Group A showed the lowest level of changes, averaging around 0.96%. Group B fell in the middle, with around 1.76% of SKUs being relocated. Group C, with the highest percentage of SKU movements, represented about 2.22% of the total number of SKUs within the group. Overall, these findings suggest certain similarities in the dynamics of SKU movements, both in the context of physical depots and different types of service recipients and ABC groups. Analyzing these patterns can contribute to a better understanding of inventory management strategies and optimization of logistic processes, which could benefit both the logistics operator and their clients. Demonstrating the SKU movements caused by dynamic ABC in comparison to traditional ABC confirmed the positive verification of the first hypothesis (H1: Dynamic ABC analysis will impact the allocation of SKUs in 3PL warehouses, i.e., inventory management strategies – confirmed). To verify the second hypothesis (H2), correlations and p-values were calculated from the collected data resulting from the conducted research. The calculated correlations according to Pearson, Spearman, and Kendall coefficients, along with p-values, categorized by individual ABC groups, physical depots, and service recipient types, are presented in table 9.

Table 9.
Correlation coefficient with p-value per ABC groups

		Correlation coefficient with p-value		
		Pearson	**Spearman**	**Kendall**
Correlation of average percentage changes in A group with	**physical depot**	|p| = 0,15 p-value = 0,28	|s| = 0,14 p-value = 0,31	|k| = 0,11 p-value = 0,31
	service recipient type	|p| = 0,09 p-value = 0,52	|s| = 0,01 p-value = 0,92	|s| = 0,00 p-value = 0,96
Correlation of average percentage changes in B group with	**physical depot**	|p| = 0,01 p-value = 0,93	|s| = 0,04 p-value = 0,78	|s| = 0,03 p-value = 0,77
	service recipient type	|p| = 0,01 p-value = 0,97	|s| = 0,14 p-value = 0,31	|s| = 0,11 p-value = 0,29
Correlation of average percentage changes in C group with	**physical depot**	|p| = 0,21 p-value = 0,13	|s| = 0,14 p-value = 0,31	|s| = 0,00 p-value = 0,97
	service recipient type	|p| = 0,04 p-value = 0,76	|s| = 0,08 p-value = 0,56	|s| = 0,06 p-value = 0,56

Source: own elaboration.

The conducted research indicated a lack of significant correlation between the analyzed variables. The absence or weak correlation, as expressed by Pearson, Spearman, and Kendall coefficients, conveys significant information about the nature of the relationship between these variables. The absence of Pearson correlation, which describes a linear relationship between variables, signals that the variables do not exhibit consistent changes in accordance with each other. As a result, it can be inferred that the variables are largely independent of each other, meaning changes in one variable do not lead to consistent changes in the other variable. The absence or weak Spearman correlation suggests that there is no clear pattern of order between the variables. This implies that the variables do not exhibit a consistent arrangement of rank values in the context of their mutual relationship. Similarly, weak Kendall correlation suggests a lack of clear order between the variables, indicating that the variables are significantly independent of each other and their mutual relationship is not clearly defined. In summary, the absence or weak correlation described by these three measures indicates a small or even missing interdependence between the analyzed variables. This suggests that these variables do not exhibit consistent behavior patterns with respect to each other, which may imply that their relationship is either random or ambiguous. Furthermore, it's worth noting that the p-value results in the case of the analyzed patterns did not reflect statistical significance. This suggests that the differences between the variables are not large enough to be considered statistically significant. Ultimately, the lack of statistical significance indicates that these differences may result from random fluctuations or variables that do not significantly influence each other. The presented results prevented a positive verification of the second hypothesis (H2: Regrouping in ABC induced by dynamic ABC exhibits correlations within physical depots and product groups). For the investigated tool, this could suggest, among other things, its stable operation regardless of the type of products and distribution networks in which it is used.

5. Discussion

5.1. Dynamic ABC as a tool for supporting the inventory management in 3PL

The conducted analysis was related to a significant transformation of the standard ABC groups, which are assigned based on a standardized procedure grounded in historical data analysis. This method aims to provide a more accurate determination of individual product groups or items based on their value or importance in the context of management and analysis. In the discussed approach, the method described in the study includes the incorporation of predictive data as a supporting element for ABC group analysis. Nevertheless, only those predictive data showing appropriate forecasting effectiveness are utilized. This means that only predictive data demonstrating a high level of consistency between forecasted values and actual outcomes are included in the analysis. Such an approach aims to ensure that predictive data used in the ABC grouping process are reliable and trustworthy. To sum up, this analysis introduces an innovative approach to determining ABC groups by utilizing proven historical data alongside precisely selected predictive data. Through this approach, ABC groups can better reflect current trends and changes in the value or significance of individual elements, contributing to more efficient resource management and decision-making. The combination of ABC with forecasting has already been applied in literature. Kartika et al. (2023) demonstrated a similar line of reasoning using examples from the pharmaceutical industry. The study's author further develops this line of reasoning in ABC classification, extending it to products from other industries and demonstrating the method's universality. The method is also applied in the case of logistics service providers who manage an assortment to which they do not formally hold ownership rights.

Within the research, the results of dynamic ABC were correlated with the outcomes of conducted XYZ analysis. This is justified due to the need to determine the degree of acceptability of forecast verifiability in the dynamic ABC method itself. However, the literature also presents other methods that, according to the author, could be considered as complements to the dynamic ABC analysis. Most frequently, the benefits of combining ABC with the VED (Vital, Essential, Desirable) method are highlighted. VED is an inventory classification method that helps identify different levels of importance or significance of items in a warehouse. The VED method assists organizations in focusing on inventory management based on its criticality to the company's operations. The significance of combining VED with ABC is shown, among others, by Amer and Jawad (2023), Gupta et al. (2007), and Ceylan and Bulkan (2017). Literature also explores modifications of VED, such as VEN (Vital, Essential, Non-essential), for situations similar to the one described. This modification is proposed, for example, by Mfizi et al. (2023). Therefore, the proposed tool carries various directions for its development.

5.2. Direction of further research and main limitation

One of the intriguing directions for tool development and further research is the integration of forecasting methods, fuzzy methods, and AHP within the framework of creating ABC. A similar logic is demonstrated, among others, in Valdivia Seminario et al. (2023). Another area to focus on in the future could be the combination of the proposed dynamic ABC with simulation models. The integration of traditional ABC with simulation models has been demonstrated, for instance, in Hidayatuloh et al. (2023), and these studies could be expanded to incorporate dynamic ABC in simulation models for warehouse management. Taking it a step further and considering the possibilities of creating Digital Twins (DT) by 3PL (Kmiecik, 2023), one can also explore the potential of supporting DT with such tools, which encompass not only historical but also predictive data.

The author is also aware of the limitations present in the conducted research. Firstly, the author has reservations about the p-values resulting from the conducted correlational analysis, which might suggest that different tests than those presented should be chosen for correlations. Additionally, the quantitative studies conducted should, according to the author, be complemented in the future by a thorough qualitative analysis of the described phenomena. Qualitative analysis could offer an interesting expansion to the conducted research.

6. Conclusions

In summary, this study focused on the analysis of a dynamic inventory classification method based on a modified ABC concept. The presented results provide a significant contribution to understanding the impact of the dynamic approach to SKU classification on inventory management within the context of a logistics operator. Through literature analysis, it becomes apparent that traditional ABC methods primarily rely on historical data, limiting their flexibility. In this context, dynamic ABC analysis, combining classification with predictive data analysis, can offer a valuable tool for enhancing inventory management efficiency. The study's findings revealed that the dynamic ABC tool led to the reclassification of a considerable number of SKUs across product groups. Although the relative percentage changes in the overall SKU count (920,557) are modest, they possess the potential to result in substantial alterations in warehouse layout and logistic process optimization. Analysis of movements within ABC groups and physical warehouses highlighted diverse trends in SKU movement across ABC groups. The introduction of the dynamic ABC tool enabled a more precise allocation of resources and improved product availability for customers. The author acknowledges the constraints inherent in the undertaken study. Firstly, there are concerns about the validity of the p-values derived from the correlational analysis, implying the need for alternative tests beyond those currently presented. Furthermore, the author proposes that future investigations incorporate a comprehensive qualitative examination of the described phenomena to complement the quantitative studies. Such qualitative analysis could provide a valuable augmentation to the conducted research. An intriguing avenue for tool development and ongoing exploration involves the amalgamation of forecasting methods, fuzzy methods, and AHP within the framework of constructing ABC. Another promising area for future emphasis could be the amalgamation of the proposed dynamic ABC with simulation models. Instances of such integration between traditional ABC and simulation models have been exemplified and these studies could be extended to incorporate dynamic ABC into simulation models specifically designed for warehouse management. Going a step further and considering the prospect of creating Digital Twins by 3PL one might explore the potential of fortifying DT with tools that encompass not only historical data but also predictive data.

It's also worth noting that the correlational analysis between variables did not exhibit significant correlations. The absence or weak correlation between different measures affirmed the limited interdependence between the analyzed variables. This suggests that the dynamic ABC tool operates stably regardless of product type and distribution network in which it is employed. Based on the study's outcomes, it can be observed that the dynamic ABC tool could present a valuable alternative to traditional inventory classification methods. It opens doors to more flexible inventory management based on predictive data analysis, potentially contributing to the enhancement of logistic operations' efficiency. Further research is also encouraged to gain deeper insights into the impact of the dynamic ABC tool on logistic operations and future innovations in inventory management.

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Appendix

Table 4.
General description of chosen case studies

country	Physical depot	Client Name	number of SKU	General type (food/non-food/pharma/other)	Brief description	shares of SKU at physical depot	shares of SKU in whole activity (PL+CZ)
PL	Physical depot 01 PL	Customer 01	160 862	nonfood	Furniture and interior furnishings.	100,00%	17,47%
PL	Physical depot 02 PL	Customer 02	369	food	Food products (e.g., juices).	0,76%	0,04%
PL	Physical depot 02 PL	Customer 03	46 269	food	Food products (e.g., sweets, beverages).	95,74%	5,03%
PL	Physical depot 02 PL	Customer 04	1 692	food	Food products (e.g., desserts, creams).	3,50%	0,18%
PL	Physical depot 03 PL	Customer 05	43	nonfood	Electronics	0,04%	0,00%
PL	Physical depot 03 PL	Customer 06	1 066	pharma	Medical products and dressings.	1,01%	0,12%
PL	Physical depot 03 PL	Customer 07	1 233	pharma	Pharmaceutical products.	1,17%	0,13%
PL	Physical depot 03 PL	Customer 08	149	pharma	Pharmaceutical products.	0,14%	0,02%
PL	Physical depot 03 PL	Customer 09	14 288	nonfood	Packaging and labels.	13,55%	1,55%
PL	Physical depot 03 PL	Customer 10	65	pharma	Pharmaceutical products and drug samples.	0,06%	0,01%
PL	Physical depot 03 PL	Customer 11	44	pharma	Pharmaceutical products.	0,04%	0,00%
PL	Physical depot 03 PL	Customer 12	538	pharma	Pharmaceutical products.	0,51%	0,06%
PL	Physical depot 03 PL	Customer 13	926	pharma	Pharmaceutical products.	0,88%	0,10%
PL	Physical depot 03 PL	Customer 14	589	pharma	Pharmaceutical products.	0,56%	0,06%

PL	Physical depot 03 PL	Customer 15	551	pharma	Pharmaceutical products.	0,52%	0,06%
PL	Physical depot 03 PL	Customer 16	65	pharma	Pharmaceutical products.	0,06%	0,01%
PL	Physical depot 03 PL	Customer 17	284	pharma	Pharmaceutical products.	0,27%	0,03%
PL	Physical depot 03 PL	Customer 18	2 809	pharma	Pharmaceutical products.	2,66%	0,31%
PL	Physical depot 03 PL	Customer 19	3 220	pharma	Pharmaceutical and cosmetic products.	3,05%	0,35%
PL	Physical depot 03 PL	Customer 20	1 885	pharma	Cosmetic and dermatological products.	1,79%	0,20%
PL	Physical depot 03 PL	Customer 21	109	pharma	Pharmaceutical products.	0,10%	0,01%
PL	Physical depot 03 PL	Customer 22	21 560	pharma	Pharmaceutical and cosmetic products.	20,45%	2,34%
PL	Physical depot 03 PL	Customer 23	74	nonfood	Cosmetic products.	0,07%	0,01%
PL	Physical depot 03 PL	Customer 24	192	pharma	Pharmaceutical products.	0,18%	0,02%
PL	Physical depot 03 PL	Customer 25	258	pharma	Healthcare and cosmetic products.	0,24%	0,03%
PL	Physical depot 03 PL	Customer 26	62	pharma	Pharmaceutical products.	0,06%	0,01%
PL	Physical depot 03 PL	Customer 27	307	pharma	Pharmaceutical products.	0,29%	0,03%
PL	Physical depot 03 PL	Customer 28	2 181	pharma	Pharmaceutical products.	2,07%	0,24%
PL	Physical depot 03 PL	Customer 29	460	pharma	Pharmaceutical products.	0,44%	0,05%
PL	Physical depot 03 PL	Customer 30	51 784	nonfood	Plumbing and bathroom fixtures.	49,11%	5,63%
PL	Physical depot 03 PL	Customer 31	317	other	Various of products	0,30%	0,03%
PL	Physical depot 03 PL	Customer 32	14	nonfood	Services related to communication and marketing.	0,01%	0,00%

PL	Physical depot 03 PL	Customer 33	20	pharma	supply for drug stores	0,02%	0,00%
PL	Physical depot 03 PL	Customer 34	21	pharma	Pharmaceutical products.	0,02%	0,00%
PL	Physical depot 03 PL	Customer 35	334	pharma	Pharmaceutical products.	0,32%	0,04%
PL	Physical depot 04 PL	Customer 36	3 455	food	a lot of food kinds, wholesaler	25,75%	0,38%
PL	Physical depot 04 PL	Customer 37	1 492	food	Food products (e.g., chocolates, cookies).	11,12%	0,16%
PL	Physical depot 04 PL	Customer 38	8 472	food	Food products (e.g., confectionery).	63,13%	0,92%
PL	Physical depot 05 PL	Customer 39	14 656	nonfood	Containers and products related to food storage.	85,04%	1,59%
PL	Physical depot 05 PL	Customer 40	119	nonfood	Finishing materials for construction and renovations.	0,69%	0,01%
PL	Physical depot 05 PL	Customer 41	2 460	food	Food products (e.g., snacks).	14,27%	0,27%
PL	Physical depot 06 PL	Customer 42	21 242	nonfood	Cosmetic and personal care products.	61,28%	2,31%
PL	Physical depot 06 PL	Customer 43	13 420	nonfood	Toys for children.	38,72%	1,46%
PL	Physical depot 07 PL	Customer 44	7 644	food	Pet products, mainly pet food.	100,00%	0,83%
CZ	Physical depot 08 CZ	Customer 45	3 093	other	tabacoo products	0,82%	0,34%
CZ	Physical depot 08 CZ	Customer 46	244	nonfood	Packaging.	0,07%	0,03%
CZ	Physical depot 08 CZ	Customer 47	8 383	nonfood	sport equipment	2,23%	0,91%
CZ	Physical depot 08 CZ	Customer 48	157	food	Food for childern	0,04%	0,02%
CZ	Physical depot 08 CZ	Customer 49	363 388	food	Products for infants and children.	96,84%	39,47%
CZ	Physical depot 09 CZ	Customer 50	56	food	Food products, may vary.	0,04%	0,01%

CZ	Physical depot 09 CZ	Customer 51	144 169	nonfood	Building materials and renovation articles.	99,96%	15,66%
CZ	Physical depot 10 CZ	Customer 52	13 467	nonfood	No specific information about the products.	100,00%	1,46%

Source: own elaboration.