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Descriptive Analysis of Supply Chain Data: Patterns, Relationships, and Strategic Insights

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Abstract:

Purpose: *The study's purpose is to conduct a descriptive analysis of supply chain data, with the goal of unveiling patterns and relationships that can inform strategic decision-making.*
Design/Methodology/Approach: *A dataset encompassing 200 observations across 17 columns—11 categorical and six numerical variables—was meticulously analyzed. The analysis included variables representing customer identifiers, sale dates, transaction values, discounts, currency, and geographical details. Data preprocessing ensured no missing values or duplicates were present, providing the robustness of subsequent analyses. Various statistical tools and visualization techniques, including histograms and correlation matrices, were employed to elucidate the data's characteristics.*
Findings: *Key findings from the dataset revealed a robust linear relationship between the net and gross values of transactions. At the same time, the quantities ordered displayed a non-linear relationship with the total value. High concentration levels were noted geographically and in customer activity, with most transactions occurring within specific locations and a limited number of customers. The data also exhibited many unique product identifiers and description values, indicating a diverse range of items within the supply chain.*
Practical Implications: *The study provides actionable insights for supply chain optimization. Recognizing patterns in transaction values and customer geography can guide strategic decisions in logistics, inventory management, and targeted marketing. Additionally, understanding product diversity and sales concentration can inform supplier negotiations and risk management.*
Originality/Value: *The research contributes to the field of supply chain management by applying a comprehensive descriptive analysis to uncover inherent data patterns. It uniquely combines various analytical techniques to draw meaningful insights with direct practical applications, particularly in enhancing the efficiency of supply chain operations and customer segmentation strategies.*

Keywords: *Supply chain, descriptive analysis, data analytics.*

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Paper type: *Research article.*

1. Introduction

Supply chain management (SCM) has become crucial in the globalized trade landscape, necessitating efficient sourcing, production, and distribution complexities handling. (Jaswanth *et al.*, 2023; 'Supply Chain Management', 2023). The importance of supply chain management has grown substantially with the advent of globalized trade and the increasing complexity of sourcing, production, and distribution networks (Tyagi *et al.*, 2023).

Descriptive analysis in supply chain management serves as a foundational step for organizations aiming to enhance operational efficiency and strategic decision-making. Researchers highlight that descriptive analysis in supply chains involves systematic data collection and analysis to identify trends, patterns, and anomalies within supply chain activities, thereby supporting more informed decision-making processes (Fang *et al.*, 2022; Jaswanth *et al.*, 2023).

Further supporting this viewpoint, Hilmola illustrates that descriptive analysis not only facilitates the understanding of the current state of supply chain operations but also aids in predicting future supply chain needs by examining historical data trends (Hilmola, 2018). This is especially relevant in the context of leveraging big data for supply chain analytics, as discussed by Riahi *et al.,* who emphasize the role of descriptive analytics in understanding past business performances to optimize future outcomes (Riahi *et al.*, 2021; Grima *et al.,* 2023; Thalassinos *et al.*, 2015).

Descriptive analysis methodologies are varied and can range from simple data aggregation and summary statistics to complex data mining techniques. Pathik et al. describe how these techniques are applied in educational supply chains to enhance resource allocation and program effectiveness, demonstrating the versatility and impact of descriptive analytics across different types of supply chains (Pathik, Chowdhury and Habib, 2012).

Incorporating artificial intelligence and machine learning into descriptive analytics, as examined by Riahi *et al.*, further extends the capabilities of supply chain management by enabling more nuanced data interpretations and predictive capabilities, which are critical for maintaining competitive advantage in fast-paced markets (Riahi *et al.*, 2021).

Advanced optimization algorithms further boost logistics efficiency. For instance, a study introduced a comprehensive algorithm to reduce transport costs and the time required for logistics tasks by incorporating the traveling salesperson problem (Golabek *et al.*, 2021; Zampeta and Chondrokoukis, 2023a; 2023b).

Additionally, predictive analytics using Long Short-Term Memory (LSTM) networks have revolutionized inventory management, enabling accurate sales forecasting and efficient stock management (Pliszczuk *et al.*, 2021). Furthermore, integrating Radio-Frequency Identification (RFID) technology with machine learning algorithms like Gradient Boosting and random forests has significantly improved order-picking accuracy and speed, enhancing logistical operations (Rymarczyk *et al.*, 2021; Velinov *et al.*, 2023).

These technologies streamline processes and support a robust supply chain infrastructure capable of real-time data analysis. These technological advances underscore the dynamic nature of supply chain management and the increasing reliance on innovations to enhance operational efficiency and competitiveness in a rapidly evolving economic landscape.

Overall, the strategic implementation of descriptive analysis in supply chain management is crucial for enhancing operational efficiencies, improving customer satisfaction, and achieving sustainable growth. As supply chains continue to evolve, the role of descriptive analysis will undoubtedly expand, becoming more integral to strategic decision-making and operational excellence in supply chain management.

The main goal of this study is to conduct a comprehensive descriptive analysis of a supply chain dataset to uncover underlying patterns and relationships that govern the dynamics between different transactional and customer variables. This study aims to identify key insights that can inform strategic decision-making processes, optimize operational efficiency, and enhance financial forecasting within supply chain management.

2. Description of the Database

The analyzed database consists of 200 observations and 17 columns, of which 11 are categorical, and 6 are numerical-type variables. The collection contains no missing data or duplicates. Figure 1 shows the first five observations from the studied dataset. Labels used in the database:

- *KlientId*: Represents the identifier of a customer.
- *DataSprzedazy*: Denotes the date of sale.
- *ZaE_GIDLp*: An integer identifier possibly representing an internal code or category.
- *Ilosc*: Refers to the quantity of items ordered.
- *ZaE_JmZ*: Indicates a unit of measure, in this case, consistently "piece" or similar, as it is uniform across the data.

- *Netto*: The net value of the transaction.
- *Brutto*: The gross value of the transaction.
- *Wartosc*: Represents the total value of a transaction.
- *ZaE_Rabat*: The discount applied to a transaction, if any.
- *Waluta*: The currency used consistently is PLN (Polish Zloty) in this dataset.
- *Knt_KodP*: Postal code associated with the client.
- *Knt_Miasto*: The city associated with the client.
- *Knt_Ulica*: The street address associated with the client.
- *TowarId*: Identifier for the goods or items ordered.
- *TowarNazwa*: The name of the goods or items ordered.
- *NowarNazwa1*: Appears to be a variant or additional description of the goods, likely providing more specific or alternate naming.

Figure 1. *The first five observations from the studied dataset: a) columns 1-12, b) columns 13-17*

a)

	KlientId	DataSprzedazy	ZaE_GIDLp	Ilosc	ZaE_JmZ	Netto	Brutto	Wartosc	ZaE_Rabat	Waluta	Knt_KodP	Knt_Miasto
0	1457	2008-04-23	1	4.0	szt.	99.0	121.77	396.0	0.0	PLN	3530	MISKOLC - HUNGARY
1	1457	2008-04-23	1	2.0	szt.	216.0	265.68	432.0	0.0	PLN	3530	MISKOLC - HUNGARY
2	1457	2008-04-23	2	12.0	szt.	122.0	150.06	1464.0	0.0	PLN	3530	MISKOLC - HUNGARY
3	1457	2008-04-23	3	7.0	szt.	144.0	177.12	1008.0	0.0	PLN	3530	MISKOLC - HUNGARY
4	1457	2008-04-23	4	6.0	szt.	144.0	177.12	864.0	0.0	PLN	3530	MISKOLC - HUNGARY
5	1457	2008-04-23	5	6.0	szt.	180.0	221.40	1080.0	0.0	PLN	3530	MISKOLC - HUNGARY

b)

Knt_Ulica	TowarId	TowarKod	TowarNazwa	TowarNazwa1
KIRALY U. 26 3 2	1861	H/KRS-MAR/POZ-CR_VV(007)-406	Krzes³o MARYNARZ POZIOMY tk.406 czer. vv (007)	Krzes³o MARYNARZ POZIOMY tk.406
KIRALY U. 26 3 2	11937	H/TOM-KS-BAREK !!!	Barek TOM kl.str/kl.str	BAREK
KIRALY U. 26 3 2	13250	H/TOM-KS-NAR !!!	Naro¿nik TOM kl.str/kl.str	NARO¯NIK
KIRALY U. 26 3 2	13502	H/TOM-KS-POD_90 !!!	Podstawka_90 TOM kl.str/kl.str	PODSTAWKA_90
KIRALY U. 26 3 2	13815	H/TOM-KS-REG.OTW_50 !!!	Rega³ otwarty_50- TOM kl.str/kl.str	REGA£ OTWARTY_50

Source: *Own creation.*

Two variables are identified as constants in the dataset due to their invariance across all entries. These variables are contained within the columns *ZaE_JmZ* and *Waluta*. Specifically, the *Waluta* variable denotes the currency used for transactions, which uniformly presents as PLN. Similarly, the *ZaE_JmZ* variable specifies the unit of measure for the number of ordered products, consistently recorded as "szt.", an abbreviation for "sztuka" in Polish, indicating that the quantity is measured in pieces. This uniformity in both variables signifies their constant nature within the dataset.

Variables such as *KlientId*, *ZaE_Rabat*, *Knt_KodP*, *Knt_Miasto* and *Knt_Ulica* exhibit a highly unbalanced distribution, where approximately 85 to 95% of the values are identical. Specifically, in the *KlientId* variable, three unique identifiers are recorded. Predominantly, identifier number 1457 accounts for 193 out of 200 cases.

Identifier number 3229 is observed six times, with the remaining instance associated with identifier number 1134. In the *ZaE_Rabat* variable, an overwhelming majority, 199 out of 200 values, are recorded as zero, with a single observation having a value of two. The variable *Knt_KodP*, representing postal codes, contains three unique values (Table 1), likely corresponding to one value per client identifier, given the presence of three unique client identifiers. The *Knt_Miasto* variable, which denotes the city, also reveals three unique values aligned with the distribution of client identifiers.

The city of Miskolc in Hungary is the predominant location, occurring in 193 out of 200 instances, representing 96.5% of the total entries. Kalwaria Zebrzydowska appears six times, accounting for 3% of the entries, and Błaszki is noted once, making up 0.5% of the occurrences. Similarly, the *Knt_Ulica* variable, related to street addresses, follows a distribution analogous to unique client identifiers—detailed values in Table 2.

Table 1. *Number and percentage of occurrences of unique values of the variable Knt_KodP*

Value	Number of occurrences	% of occurrences
3530	193	96.5
34-130	6	3
98-235	1	0.5

Source: *Own creation.*

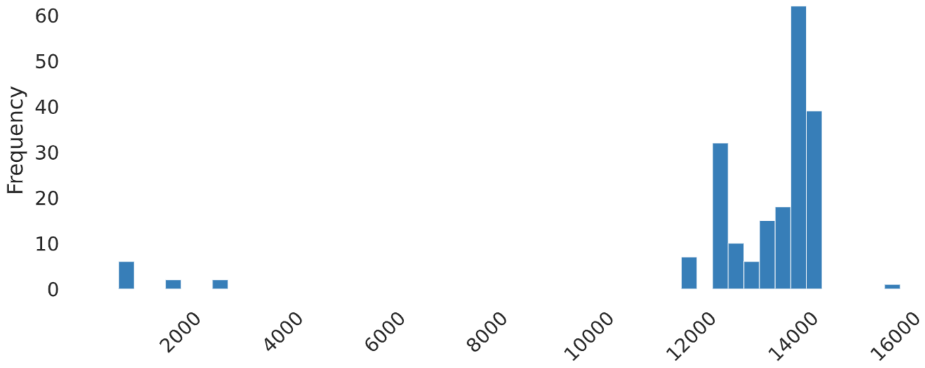
Table 2. *Number and percentage of occurrences of unique values of the variable Knt_Ulica*

Value	Number of occurrences	% of occurrences
KIRALY U. 26 3 2	193	96.5
Królowej Jadwigi 2	6	3
ul. Sieradzka 41	1	0.5

Source: *Own creation.*

The variable *TowarId* serves as the identifier for ordered products. These identifiers are positive integers ranging from 771 to 16072. Within this column, there are 198 unique values. The identifier number 14044 is the only one that repeats, occurring three times; all other identifiers are unique. Figure 2 displays a histogram of the *TowarId* variable. As these are identifiers rather than values, they do not distribute in a manner typical for numeric variables. It is observed that most ordered products possess identifiers approximately between 12000 and 14000.

Figure 2. *Histogram of the variable TowarId*



Source: *Own creation.*

TowarKod, *TowarNazwa*, and *TowarNazwa1* exhibit a significant number of unique values, ranging from 173 to 198 out of 200 observations, with even distributions across the variables. *TowarKod* is analogous to *TowarId* but differs in that while the identifier is numeric, the code comprises numbers, letters, and characters. A specific code, H/CL/SA-OFI-SZW2D_O, repeats three times, while each other code appears only once within the dataset. *TowarNazwa* shows a distribution similar to that of *TowarId* and *TowarKod*. The name SZW2D_O CLIPPER/SALSA fineline repeats three times.

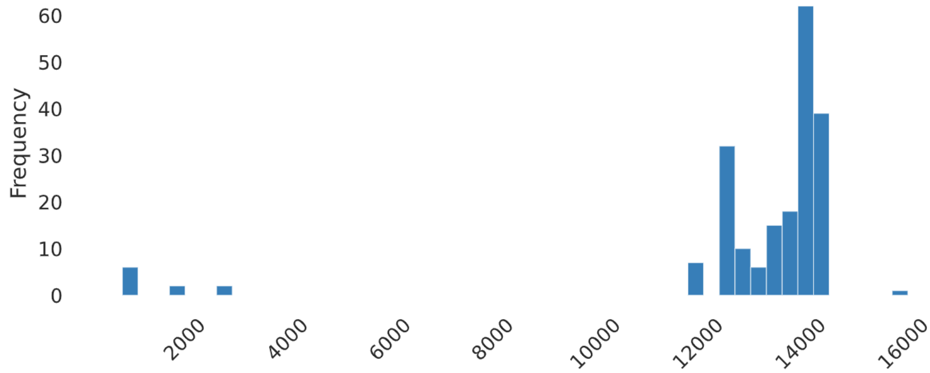
Example names of goods include PPK110 AMELIA antique pine, Barek 80 WIKTOR dark apple, and KOM1d1sn AMELIA antique pine. *TowarNazwa1* is a variable similar to *TowarNazwa*, but the product names are more generic. This column presents 173 unique values. The values SZAFKA_4s and SZW2D_O CLIPPER/SALSA appear three times each. Several values appear twice in the column, such as WIKTOR WARDROBE, WIKTOR BASE DRAWERS 70 (CHEST), and HPOL/12.

The variable *DataSprzedazy* denoting the date of sale, exhibits five unique values. The data encompasses dates from April and August of the year 2008. The most frequently occurring date within the dataset is April 23, 2008, which appears 78 times, accounting for 39% of occurrences. This is followed by April 25, 2008, with 56 instances or 28%. On August 13 and August 28, 2008, each recorded 29 occurrences, contributing 14.5%. The least common date is April 24, 2008, presenting only eight times, corresponding to 4% of the data.

The variable *ZaE_GIDLp* comprises positive integers and contains 33 unique values ranging from 1 to 33. Figure 3 displays a histogram of this variable. The primary statistical indicators are: Minimum: 1, Maximum: 33, Mean: 11.2, Median: 10, Standard Deviation: 7.659, Kurtosis: -0.403, Mean Absolute Deviation: 6, Skewness: 0.573.

Based on the histogram and the skewness value, it can be inferred that *ZaE_GIDLp* exhibits right-skewed asymmetry, indicating that lower values of the variable occur more frequently than higher values. The distribution of variable values tends to be close to decreasing, except for the observation at value 18. The mean slightly exceeds the median, though these values are relatively close, 11.2 and 10, respectively. The negative kurtosis suggests a lesser concentration of values around the mean.

Figure 3. *Histogram of the variable ZaE_GIDLp*



Source: *Own creation.*

The variable *Ilosc* represents the quantity of products ordered, accepting positive integer values ranging from 1 to 12. Approximately 60% of the instances assume a value of 1. The mean of this variable is 1.975, with a median of 1, indicating a concentration of values near these figures. The variable *Netto* represents the net value of an order, consisting of positive real numbers ranging from 23 to 1452. The median value is 201, with an average of approximately 250.

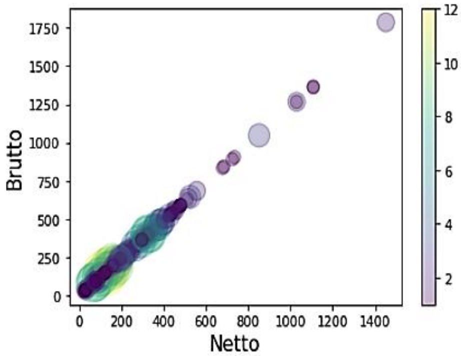
The variable *Brutto* denotes the gross value of an order. Its distribution shares characteristics similar to those of the *Netto* variable. The *Brutto* values are positive real numbers that range from 28.29 to 1785.96, with an average of approximately 308, which exceeds the median value of 247.23. The variable *Wartosc* includes positive real numbers within the range of 23 to 2904.

The distribution of this variable resembles those of the *Netto* and *Brutto* variables. The average value is around 467, whereas the median is significantly lower at 296. The standard deviation is over 500, indicating a broad spread of values around the mean. The data set has high correlations between variables such as *Ilosc*, *Wartosc*, *Netto*, and *Brutto*.

3. Descriptive Analysis of the Database

Based on the descriptive analysis of variable interactions and dependencies within the dataset, the most pronounced and significant relationships have been delineated as follows. A conspicuous linear relationship exists between the *Netto* (net value) and *Brutto* (gross value) variables.

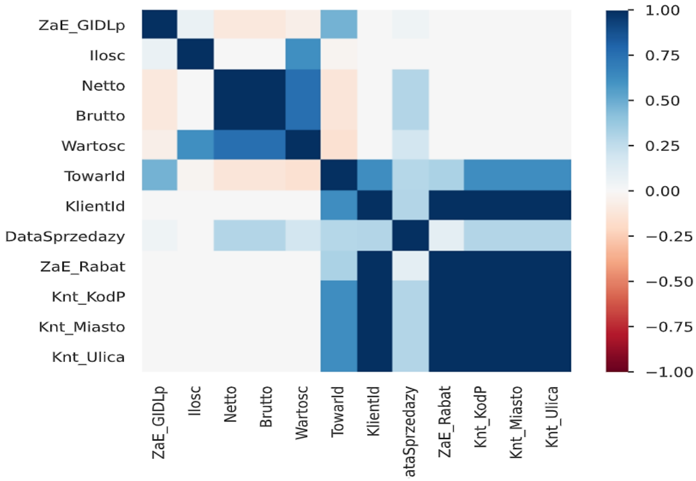
Figure 4. *Relationship between Netto and Brutto with the variable Ilosc*



Source: *Own creation.*

As illustrated in Figure 4, this linear dependency is visually apparent, and correlation analysis further substantiates this with a correlation coefficient of 1, as seen in Figures 5 and 6. This suggests redundancy between these two variables, indicating one might be excluded in further statistical model constructions to prevent multicollinearity.

Figure 5. *Correlation matrix between variables in the studied set (heat map)*



Source: *Own creation.*

Figure 6. *Correlation matrix between variables in the studied set (numerical values)*

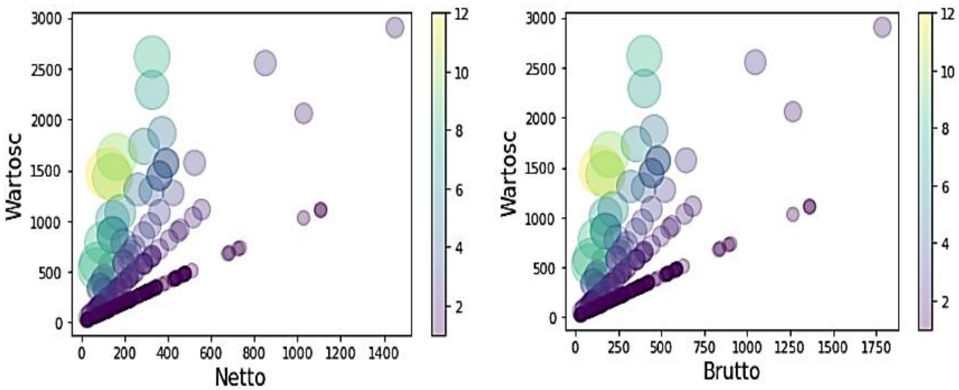
	ZaE_GIDLp	Ilosc	Netto	Brutto	Wartosc	TowarId	KlientId	DataSprzedazy	ZaE_Rabat	Knt_KodP	Knt_Miasto	Knt_Ulica
ZaE_GIDLp	1.000	0.068	-0.104	-0.104	-0.056	0.476	0.000	0.046	0.000	0.000	0.000	0.000
Ilosc	0.068	1.000	0.003	0.003	0.613	-0.031	0.000	0.000	0.000	0.000	0.000	0.000
Netto	-0.104	0.003	1.000	1.000	0.756	-0.119	0.000	0.292	0.000	0.000	0.000	0.000
Brutto	-0.104	0.003	1.000	1.000	0.756	-0.119	0.000	0.292	0.000	0.000	0.000	0.000
Wartosc	-0.056	0.613	0.756	0.756	1.000	-0.150	0.000	0.181	0.000	0.000	0.000	0.000
TowarId	0.476	-0.031	-0.119	-0.119	-0.150	1.000	0.621	0.282	0.318	0.621	0.621	0.621
KlientId	0.000	0.000	0.000	0.000	0.000	0.621	1.000	0.294	0.997	1.000	1.000	1.000
DataSprzedazy	0.046	0.000	0.292	0.292	0.181	0.282	0.294	1.000	0.098	0.294	0.294	0.294
ZaE_Rabat	0.000	0.000	0.000	0.000	0.000	0.318	0.997	0.098	1.000	0.997	0.997	0.997

Source: *Own creation.*

Moreover, the relationship between the order value (*Wartosc*) and the *Netto* and *Brutto* values shows multiple rising linear trends without a singular dominant trend, as observable in Figures 7a and 7b. Figure 7a highlights the relationship between *Netto* and *Wartosc* (value), incorporating the variable *Ilosc* (quantity), where a significant increase in order sizes corresponds with value levels around 1500.

This is mirrored in the interaction between *Brutto* and *Wartosc*, as depicted in Figure 7b, suggesting larger order sizes typically correspond with smaller values of *Netto* and *Brutto*. The correlation matrix reveals a substantial correlation of 0.756 between these variables, significant yet not compelling enough to necessitate the exclusion of any variable without further analysis to confirm redundancy.

Figure 7. *Relationship between the variable Wartosc (including the Ilosc) and the variable: a) Netto, b) Brutto.*



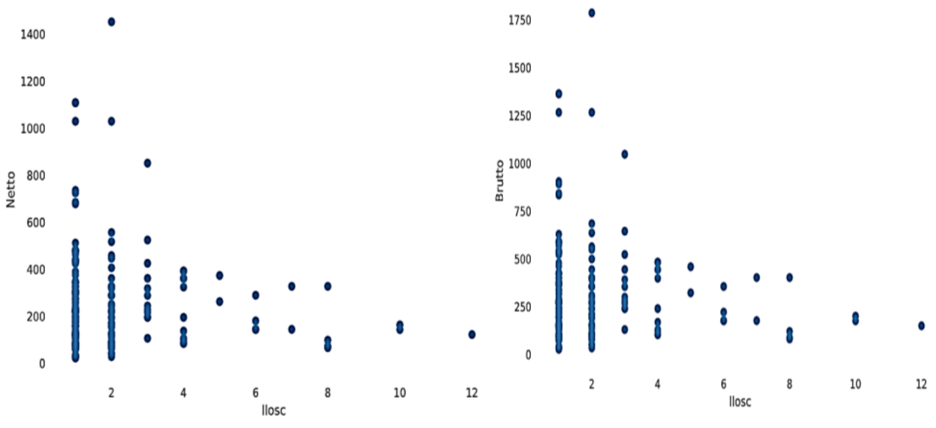
a) *b)*

Source: *Own creation.*

Additionally, the interactions between quantity and net and gross values show few orders with large products, typically ranging from 1 to 3 (Figure 8). In scenarios with small quantities, the order value exhibits considerable variability, whereas with large amounts, orders' net and gross values tend to be relatively low.

The correlation analysis suggests no linear correlation between product quantity and net/gross values, as the correlation coefficient is near zero. This suggests a potential non-linear relationship might exist, warranting further investigation.

***Figure 8**. Relationship between Ilosc and the variable:a) Netto, b)Brutto*



Source: *Own creation.*

Among the explored interactions, a mild tendency is observed where larger quantities in an order correlate with a higher total order value, albeit with considerable fluctuations in cases of small amounts. The linear correlation coefficient between these variables is 0.613, indicating that as one variable increases, so does the other.

Other variables in the correlation matrix, such as 'ZaE_GILDp', 'TowarId', 'KlientId', 'DataSprzedazy', and 'ZaE_Rabat', do not undergo analysis for functional dependencies as they are categorical variables, identifiers, and dates despite being represented numerically.

4. Conclusions

This study's descriptive analysis of supply chain data has identified several crucial insights pertinent to understanding the dynamics of customer behavior and product management within the database. The potential applications of these analyses in supply chain decision-making are extensive and multifaceted. Supply chain managers can refine financial forecasting and risk assessment processes by understanding the significant linear relationships between key financial metrics such as net and gross values. The redundancy noted between these variables can lead to streamlined data collection and analysis processes, reducing operational costs and improving the speed of decision-making.

Moreover, the insight into the non-linear relationship between the quantity of products ordered and the total order value offers a robust foundation for enhancing inventory management strategies. Managers can utilize these findings to adjust stock levels dynamically, optimize reorder points, and better align inventory with demand patterns, thereby minimizing holding costs and reducing the risk of stockouts or overstock situations.

As revealed through the analysis, the geographical concentration of sales and customer activities provides a strategic advantage in optimizing logistics and distribution networks. Companies can enhance their distribution logistics by focusing on regions with higher sales volumes, potentially centralizing warehousing in these regions to reduce delivery times and costs. This regional focus can also guide targeted marketing campaigns and customer engagement strategies, tailored to customers' specific preferences and behaviors in these areas.

Furthermore, analyzing discount strategies and their limited use offers valuable insights for sales and marketing departments. Understanding the impact of current pricing strategies on sales volumes can guide pricing policy adjustments, potentially increasing targeted discounts to boost sales during slower periods or in less active markets.

In the broader context of supply chain management, descriptive analysis acts as a critical tool for risk management. By identifying patterns and correlations within transaction data, supply chain managers can more effectively anticipate potential disruptions and bottlenecks. For instance, if certain products frequently lead to high gross values but are linked with supply inconsistencies, managers can proactively seek alternative suppliers or develop contingency plans to mitigate these risks.

Overall, applying descriptive analytics in supply chain decision-making enhances operational efficiency and financial performance and contributes to a more agile and responsive supply chain. Such analytics empower managers to make informed decisions backed by data, improving sustainability and competitiveness in the marketplace.

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