Comparison of expert and algorithmic analysis of efficiency evaluation of inventory management systems

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Abstract

This paper explores factors affecting inventory management efficiency in retail and proposes a mathematical model for describing stock changes due to non-systemic events. It also presents an ideal inventory system model and a matrix of correspondence between the quantitative impact of events and the deviation of stocks from the ideal model. Particular attention was paid to comparing the estimates provided by experts with the results of algorithmic analysis. This analysis was conducted using large volumes of data from a real retail network. The results obtained show significant differences between the experts' estimates and the data obtained from the system analysis. This confirms the effectiveness of the proposed formalized approach. The described method increases the accuracy of identifying sources of lost sales and overstocks by 2-5 percent, as well as optimizing solutions in inventory management systems by formalizing and automating manual processes.

Keywords

inventory management efficiency, information system, expert system, forecast, Big Data

1. Introduction

Demand forecasting is a fundamental process in inventory management information systems [1, 2]. It directly impacts financial and logistics performance. Both statistical (e.g. Moving Average, Exponential Smoothing, ARIMA and SARIMA) and machine methods (e.g. neural networks, Random Forest and Gradient Boosting) are used for forecasting [3]. Each method has its own advantages: the Moving Average, Exponential Smoothing and ARIMA methods are easy to implement in finance (e.g. stock market analysis), economic forecasting and supply chain management [4], the SARIMA method can take seasonality into account [5], neural networks can process large amounts of data and automatically detect patterns [6]. However, they all have limitations, such as lagging trends and limitations in non-linear cases when using statistical methods [7], and computing requirements for machine learning [8].

Overstock and lost sales are key indicators of the inefficiencies in existing information systems and software, which arise from inaccurate forecasts and imperfect business processes. The effectiveness of information systems and inventory management software should be analyzed in terms of statistical, logistical, financial and behavioral aspects. Efficiency is influenced by a wide range of factors, such as forecast accuracy, supplier reliability and logistical constraints. All these factors interact with each other to determine the extent to which the system can ensure the availability of goods at minimal cost. In existing methods for assessing the quality of information systems, the influence of these factors is determined by expert heuristic assessment [9]. However, heuristic methods have significant drawbacks, including subjectivity, poor scalability and poor formalization [3]. Therefore, these methods must be supplemented or replaced entirely by formalized computational models to ensure transparency, adaptability, and scalability in information systems.

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2. Related works

Effective inventory management involves reducing costs, optimizing resource usage and ensuring an uninterrupted supply of goods or raw materials. This should be taken into account when developing new inventory management information systems and software. The effectiveness of inventory management information systems is analyzed using various algorithms and forecasting methods, including classical mathematical models, optimization methods, and machine learning algorithms [10, 11].

Any forecasting methodology contains an element of error that can significantly impact the efficiency of the supply chain. If forecast errors fluctuate widely, it becomes more difficult to manage inventory because the required order volumes cannot be predicted. This leads to instability in production and logistics planning, frequent order adjustments and an increased risk of erroneous procurement decisions [3].

Reducing forecast errors helps to optimize costs, improve service levels and boost financial performance. The following methods have been identified as ways to reduce the forecasting error:

1. Use the correct forecasting method for each product and case.
2. Dynamic inventory adjustment (just-in-time, JIT). The JIT method involves purchasing goods only when needed, which reduces the risk of overstock [12].
3. Integrating forecasting with the supply chain by using joint forecasting between suppliers and retail chains [13].

Two of the main problems that arise in the process of supply chain management are lost sales and overstock [14, 15]. The extent of lost sales and overstock depends on the accuracy of forecasts as well as various internal and external factors affecting demand, supply, and resource management.

Existing methods of factor analysis consider various classifications of factors affecting the efficiency of the inventory management system, including source of occurrence, nature of influence, controllability, duration of influence, and functional area [16, 17, 18, 19]. There is a cause-and-effect relationship between factors and overstock or lost sales. To determine this relationship, it is necessary to classify the factors according to the order in which the events occur, as these events affect changes in inventory levels [20].

Using methods and algorithms to analyze the effectiveness of management systems ensures a balance between inventory levels, maintenance costs, and customer satisfaction. The effectiveness of inventory management information systems is analyzed using quantitative and qualitative methods, such as the economic order quantity method, ABC-XYZ analysis, storage cost analysis, and lost sales and overstock analysis [12, 21, 22, 23, 24].

The effectiveness of an inventory management information system depends on various parameters, such as forecasting accuracy and financial constraints, as well as the impact of external and internal factors. However, existing methods provide only an indirect link between the results of the inventory management system and the factors that influenced them [20].

3. Problem statement

Conduct a comparative analysis of the impact of factors on the effectiveness of the inventory management information system. Use expert opinion and a formalized model of the impact of events on the inventory balance to identify deviations in the form of lost sales and overstocks, and determine their causes.

4. Proposed work

To determine the cause-and-effect relationship, it is necessary to classify the existing factors according to the order in which events affecting inventory levels occur [20]. The main goal of inventory management, which involves controlling, planning, and managing the volume of goods stored in warehouses, is to

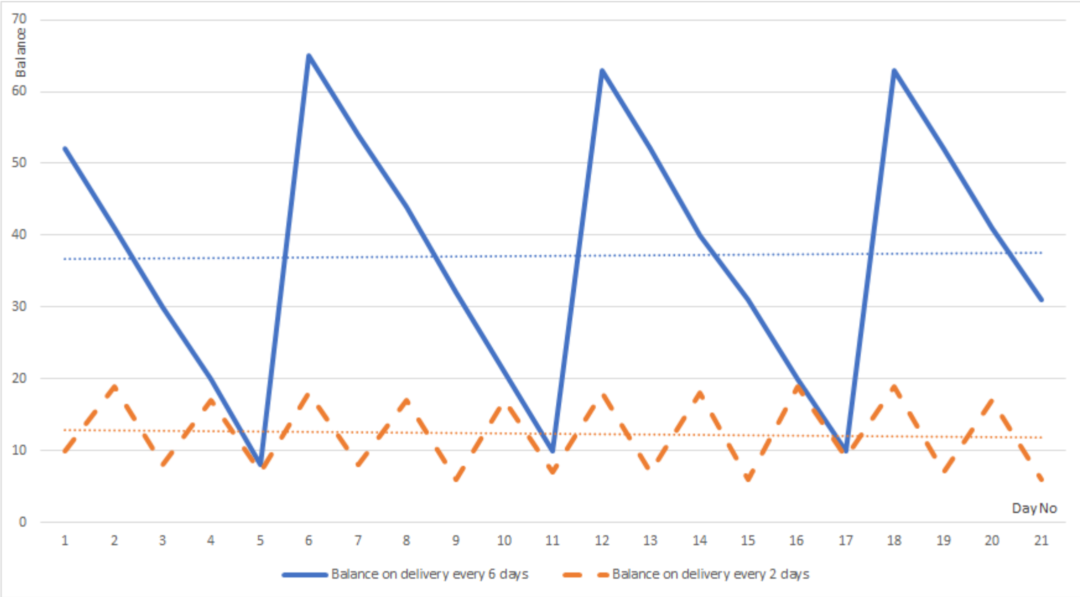

Figure 1: Dependence of inventory levels on order frequency.

reduce storage costs and maintain a high level of customer service [25]. Thus, an inventory management information system aims to keep stock within optimal limits to prevent lost sales and overstock. Essentially, the inventory management process manages inventory levels and covers several stages that are automated by modern information systems.

The volume of deliveries depends on how often and when the goods need to be ordered and how long it takes to fulfill the order. These conditions are determined by the order schedule (Figure 1). The order schedule shows order frequency and delivery volumes and is used to optimize inventory management.

The main parameters of the order schedule are [26, 27]:

1. Order Frequency / Order Interval. This is the time interval between two consecutive orders. It can be fixed (for example, once a week) or variable (depending on demand).
2. Lead Time. The period between placing an order and actually receiving the goods. Longer Lead Time needs earlier initiation an order to avoid a shortage.
3. Safety Stock. This is an additional amount of goods that is held to protect against fluctuations in demand or delays in delivery. It is not used under normal conditions, but is activated in critical situations.
4. Order Quantity. This is the quantity of goods that is ordered in one cycle.
5. Transit. This is an order that has already been placed but has not yet been received. In the order schedule, it is displayed as a planned increase in inventory in the future.

In general, the equation for changing the balance can be written as [28]:

$$S_t = S_0 + \sum_{i=1}^{t-1} d_i \tag{1}$$

where S_0 – is the initial balance, $d_i > 0$ - events that increase the inventory: deliveries, returns, error corrections, detection of overstock, etc., $d_i < 0$ - events that decrease the inventory: sales, losses, theft, error corrections, return to supplier, write-offs, etc. Events occur in chronological order: $t_1 < t_2 < \ldots < t_n$.

The authors propose the following ideal model of the process of the inventory management information system. It can be described as follows:

1. Orders are placed on schedule and nothing is missed.
2. The information system accurately forecasts and calculates the initial order of goods.

3. The initial order is sent to the supplier.
4. The order is fulfilled by the supplier on time and in full.
5. The goods appear on the store shelves on time.
6. Sales data is entered into the information system on time and accurately.

The events that increase and decrease the balance in the ideal model are deliveries and sales:

$$d_t = Q_t - p_t, \tag{2}$$

where Q_t – deliveries in the period t, p_t – sales in the period t. In the proposed ideal model, the initial order of goods is fulfilled by the supplier on time and in full. If the order lead time is LT, then the supply is Q_t = O_{t-LT}, where O_{t-LT} – is the initial order. The order must provide the store with goods from the delivery date to the next delivery date. Therefore, the order O_{t-LT} is proposed to be expressed as follows:

$$O_{t-LT} = (\sum_{i=t}^{t+F} f_i \ + q - PS_t)^+, \tag{3}$$

where $x^+ = max(0; x)$, $t - LT$ – is the date of ordering the goods, t - is the date of delivery of the goods, LT – is the time for order fulfillment, F – is the number of days until the next delivery, q – is the quantity for visual representation of the goods, f_i – is the forecast sales, PS_t - is the planned balance of the goods on the date of delivery, which is calculated as follows:

$$PS_t = (S_{t-LT} - \sum_{i=t-LT}^{t-1} f_i)^+, \tag{4}$$

where S_{t-LT} is the balance of the goods on the date of the order.

In the proposed ideal model of operation, the information system makes an accurate forecast, then $f_i = p_i$. Thus, formulas (3) and (4) are reduced to a system of equations that reflects the residual in the ideal model:

$$S_t = \begin{cases} q + \sum_{i=t}^{t+F} p_i, if:\ S_{t-LT} \leq \sum_{i=t-LT}^{t+F} f_i + q \\ S_{t-LT} - \sum_{i=t-LT}^{t-1} p_i, else. \end{cases} \tag{5}$$

It should be noted that the situation in the ideal model when the S_{t-LT} residual is greater than $\sum_{i=t-LT}^{t+F} f_i + q$ is a special case of the initial conditions with which the model starts to work. This residual will gradually decrease until it falls within the optimal limits. Thus, the balance S_t of the ideal model is equal to the quantity for the visual representation of the product q plus the forecasted sales f_i from the current date to the date of the next delivery. The basic equation of the balance in the ideal model is:

$$S_t = q + \sum_{i=t}^{t+F} p_i \tag{6}$$

Unlike the ideal model, the operation of an information system in real life is affected by factors R_t, that increase or decrease the residual of the ideal model. The factors affecting lost sales or overstock in period t can be represented as follows [20]:

$$R_t = \begin{bmatrix} id_1 & id_2 & ... & id_k \\ n_1 & n_2 & ... & n_k \\ r_1 & r_2 & ... & r_k \end{bmatrix}, \tag{7}$$

where R_t – is the set of factors that influenced the performance indicator in period t, k – is the number of factors that influenced the performance indicator in period t, n – is the sequence number of the factor occurrence, id_i – is the identifier of the factor that characterizes the reason for its occurrence, r_i – is the quantitative impact on the balance of the goods by how much the balance decreased or increased compared to the balance of the ideal model.

The following residual equation is proposed to take into account the influence of the factors:

$$S_t = q + \sum_{i=t}^{t+F} p_i + \sum_{i=t-LT}^{t-1} R_i, \tag{8}$$

A lost sale is the absence of a product, i.e. S_t = 0. Thus, lost sales result when the following inequality holds:

$$-\sum_{i=t-n}^{t-1} R_i \geq q + \sum_{i=t}^{t+F} p_i\ , \tag{9}$$

where R_i – quantitative impact that reduces the residuals of the ideal model due to the influence of factors, n – the number of days before the date of the nearest order that should arrive in the period t.

Overstock is the excess of the target inventory level T_t, which is determined by the formula:

$$T_t = max(\sum_{i=t-LT}^{t+F} p_i\ ; P) + q, \tag{10}$$

where T_t – target inventory level, P – multiplicity of delivery of goods.

Converting formulas (8) - (10) to a single equation, we obtain the inequality that leads to overstock:

$$\sum_{i=t-n}^{t-1} R_i \geq \begin{cases} \sum_{i=t-L_T}^{t-1} p_i, & \text{if } \sum_{i=t-L_T}^{t+F} p_i > P, \\ P - \sum_{i=t}^{t+F} p_i, & \text{otherwise.} \end{cases} \tag{11}$$

The influence of factors on the performance indicator for a given set of factors R_t can be represented as a correspondence matrix CR_t, which shows the relationship between the performance indicator and the factors that influenced it [20]:

$$CR_t = \begin{bmatrix} id_1 & id_2 & ... & id_k \\ cr_1 & cr_2 & ... & cr_k \end{bmatrix}, \tag{12}$$

where CR_t – factors that influenced the performance indicator in period t, cr_i – quantitative value of the factor that influenced the performance indicator. The impact on the current state of the balance S_t is determined by the sum of all events up to the moment of analysis. Since the events occur in chronological order, later events id_i have a direct and decisive impact on the current level of the balance [20].

5. Results and discussion

Data from one of Ukraine's largest retail network, which sells cosmetics, perfumes, and health and care products, was analyzed for 2024. The network has more than a thousand stores and an average assortment of 7,800 products.

The influence of factors on the efficiency of inventory management systems was determined using two methods:

- by a group of experts using the heuristic method
- by the method of determining CR_t - calculation of the impact of factors on lost sales and overstock

Table 1
Comparison of the Assessment of the Impact of Factors on Lost Sales Based on the Results of Expert Assessment and Calculation

Factors affecting lost sales	Expert estimate, %	Calculation results, %
The supplier fulfilled the order with a smaller volume	40,3%	22,3%
Reducing the order to ensure a logistics batch	0,0%	12,6%
The order was reduced or canceled manually by the manager	5,0%	22,1%
Forecast error	48,2%	19,5%
Introduction of a new product to the assortment	0,0%	10,8%
A sharp increase in demand due to shelling, lack of electricity	2,0%	8,5%
Decrease in the balance due to inaccurate information	0,0%	1,2%
Other reasons	4,5%	3,0%

The following factors affecting lost sales were analyzed:

- The supplier fulfilled the order with a smaller volume.
- Reducing the order to ensure a logistics batch.
- The order was reduced or canceled manually by the manager.
- Forecast error
- Introduction of a new product to the assortment
- A sharp increase in demand due to shelling, lack of electricity, etc.
- Decrease in the balance of goods due to inaccurate information in the information system.

The results are presented in Table 1.

Figure 2 shows the scatter plot illustrating the discrepancy between the expert and calculated estimates of the impact on lost sales.

The points on the y=x line represent factors for which the expert opinion and the calculation exactly match. The closer the points are to this line, the greater the agreement between the two methods. Points above the line ($y > x$) represent factors that the experts underestimated, whereas the calculation showed a much greater impact. This indicates hidden or underestimated systemic problems, which are revealed by detailed calculation analysis. These are key areas for further research and for correcting management decisions. Points below the line ($y < x$) are factors that experts overestimated; the calculation showed a smaller impact. This may indicate an emotional perception or a focus on the most visible, but not necessarily the most significant, problems.

Based on the obtained values, we can conclude that experts overestimate the supplier's performance for smaller volumes by more than twofold. Possible reasons include the emotional effect and recent incidents. When the order was reduced to create a logistics batch, the calculation revealed an impact that the experts had not considered. The calculation also indicates serious managerial losses that the experts may have underestimated when the manager manually reduced or canceled the order. According to the experts, the main reason for lost sales is the forecast error. However, the calculation shows that the impact of the forecast error is 28.7% lower due to more accurate and complete data. The calculation revealed the impact of new product launches, which the experts did not record, as well as a greater effect of demand surges than the experts expected. The inaccuracy of the information system has a minimal impact that was also overlooked by the experts.

The impact of the following factors on overstock was assessed:

- Manually increasing an order by a manager
- Increasing an order for a logistics batch
- Data errors
- Removing an item from the assortment
- Reducing the quantity for visual representation of the item
- Forecast error

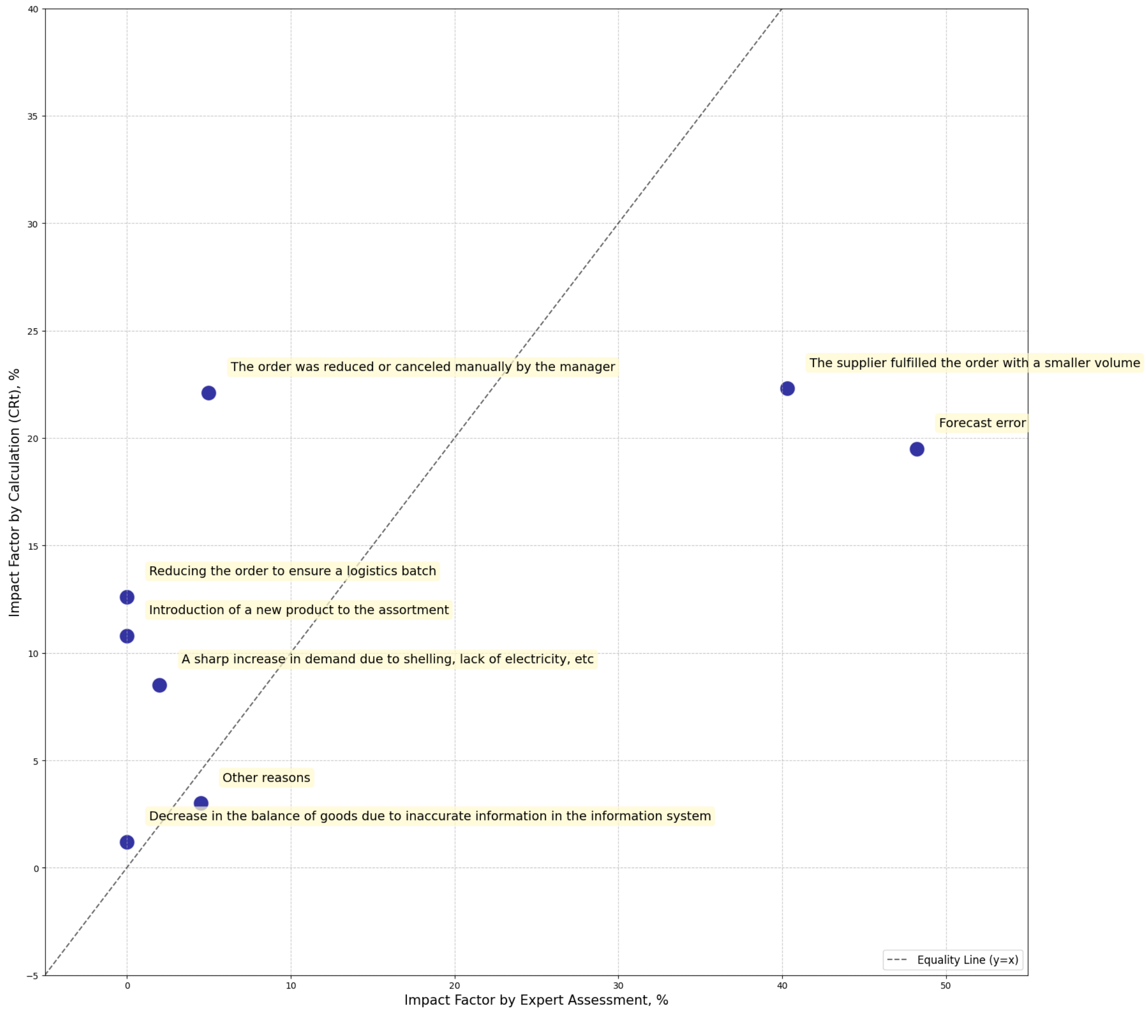

Figure 2: Comparison of expert assetments and calculated impact on lost sales.

Table 2
Comparison of the Assessment of the Impact of Factors on Overstock Based on the Results of Expert Assessment and Calculation

Factors affecting overstock	Expert estimate, %	Calculation results, %
Manually increasing an order by a manager	12,7%	31,6%
Increasing an order for a logistics batch	5,0%	22,9%
Data errors	0,0%	11,5%
Removing an item from the assortment	5,0%	7,0%
Reducing the quantity for visual representation of the item	2,0%	5,4%
Forecast error	49,2%	19,9%
The supplier fulfilled the order in a larger volume than ordered	21,0%	1,1%
Other reasons	5,1%	0,6%

- The supplier fulfilled the order in a larger volume than ordered

The results are presented in Table 2.

As shown in Figure 3, the scatter plot illustrates the discrepancy between the expert and calculated estimates of the impact on overstock.

The comparison shows that experts overestimate the role of inaccurate forecasts by 29.3%. Meanwhile, the calculation revealed a significant impact of manual intervention in order placement, a factor that experts underestimated by 18.9%. The calculation did not take into account potential errors in the

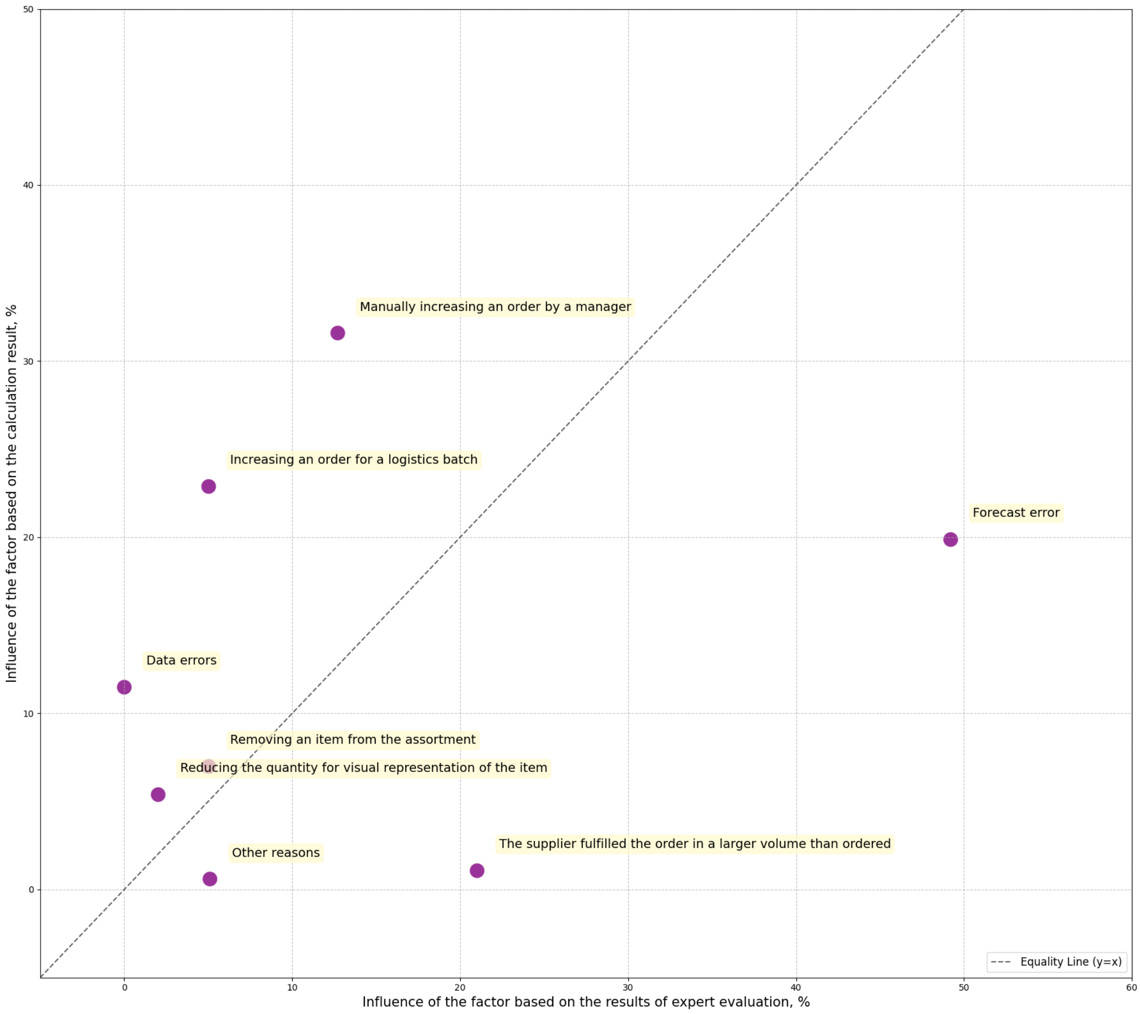

Figure 3: Comparison of expert assetments and calculated impact on lost sales.

information system that were identified. Experts consider delivering more supplies than ordered to be a systemic problem. However, the calculation data show that this judgment is erroneous. This is due to the hidden influence of logistics rules revealed by the calculation.

Experts tend to overestimate forecast errors and supplier influence. However, the calculation reveals a more balanced structure of factors, including order changes due to logistics rules and manual intervention. The data shows that expert judgment reflects an intuitive view of the main factors, which is often focused on the most visible or recurring events. In contrast, the calculation provides a more objective, structured analysis that identifies hidden, systemic, and cumulative impacts overlooked by experts.

Despite the availability of modern information systems and forecasting algorithms, the causes of these inefficiencies are often identified using estimates from an expert system. These estimates are subjective and not always representative. This reduces the accuracy of management decision-making and makes it difficult to build objective accounting models. Conversely, formalized mathematical models that account for the quantitative impact of events such as sales, deliveries, returns, and accounting errors on balance dynamics are not widely used by trading enterprises.

6. Conclusions

The study emphasizes the importance of using a formalized approach to analyze the factors affecting the efficiency of inventory management systems. The article considers events impacting inventory balance changes and builds a mathematical model identifying events leading to lost sales and excess inventory as deviations from the ideal inventory management model.

The proposed model takes into account both events that reduce inventories (sales, returns to suppliers, theft, etc.) and those that increase them (deliveries, returns from customers, correction of accounting errors, etc.). For each event, a quantitative impact is determined, which allows you to form a matrix of correspondence between factors and deviations from the expected inventory level.

This study conducts a comparative analysis of the impact of various factors on the efficiency of inventory management systems. It also presents a method for calculating the impact of these factors on lost sales and overstocks. Calculations and expert evaluations were performed using real, impersonal data from one of the Ukrainian retail network. Particular attention is paid to comparing expert assessments with the results of algorithmic analyses. As the article shows, experts tend to focus on the most visible or recurring causes (e.g., forecast errors or supply reliability), whereas the algorithm identifies hidden, systemic sources of problems related to management actions, logistical constraints, and errors in the information system.

Thus, it is an urgent scientific and practical problem to develop a formalized model of the impact of events on inventory balance. This model would allow us to identify deviations in the form of lost sales and overstocks, determine their causes, and compare the effectiveness of expert and automated approaches to analysis. This topic is planned for further research.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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