Artificial Intelligence Effects on Inventory Planning of Sensitive Products

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Abstract Pharmaceutical companies invested heavily in research and development, nowadays their funds are mostly allocated in the supply chain management. Inventory forecasting using AI focuses on optimising supply chain processes and mitigating operational risks related to the treatment of sensitive products. The purpose of this research is to comprehensively examine the processes and important factors that influence the implementation of forecasting and optimising inventories. The objectives identify data sources, examine data information flows, review appropriate forecasting models and analyse inventory optimisation-related metrics that could be applied in manufacturing companies. In this paper, the authors review the latest literature in the areas of sales forecasting, inventory optimisation and related forecasting models and metrics, with special emphasis on AI models. The literature review includes publications of scientific research results as well as reports on the development results of the applied inventory optimisation solutions in the industry. The research results will be useful for conducting applied research in a selected company, addressing the complex issue of managing a supply chain, as well as the production and storage of perishable materials and products. Results will be useful in research aimed at improving the forecasting of the inventory of sensitive products and consequentially increasing business efficiency.

Keywords:
inventory planning,
manufacturing optimisation,
sales forecasting,
artificial intelligence,
pharmaceutical industry,
supply chain

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1 Introduction

The development of technology has enabled individuals and companies to collect and use huge amounts of data in their operations. The data collected are often unstructured, thus efforts are made to structure it as much as possible and provide it to the relevant users in real-time in the form of information. For a smooth flow of information, it is necessary to establish mechanisms, technologies and processes in a company that detect important data and distribute it properly to the departments involved (Kubinaa, Varmus, & Kubinova, 2015; Weißhuhn & Hoberg, 2021).

Successful pharmaceutical companies deal with very sensitive products, thereby they place great emphasis on optimising supply chain processes. The products must be placed on the market as quickly as possible so that they are not subject to temperature fluctuations during excessive storage, which could pose a risk to product quality. Prolonging storage or shipping increases the likelihood of product damage or decay, which can endanger consumer health and at the same time increase the manufacturers' costs due to a market recall (Nguyen, Lamouri, Pellerin, Tamayo, & Lekens, 2021; Shapiro & Wagner, 2009; Shah, 2004).

At the same time, storage capacities for pharmaceutical products are very expensive, as specific and durable storage temperature conditions must be safeguarded. As a result, pharmaceutical companies strive to forecast inventory levels as much as possible by applying artificial intelligence (AI) models to accurately predict inventory levels of raw materials and finished products. Lack of product quantity on the market can pose a serious threat to human health in the pharmaceutical industry. On the other hand, excessive inventory levels can have a financial impact on the production company, as the products are discarded after the expiry date (Nguyen, Lamouri, Pellerin, Tamayo, & Lekens, 2021). Inventory fluctuations can have legal consequences (lawsuits and restitutions) and negatively affect market investors (Fahimnia, Tang, Dearzani, & Sarkis, 2015).

The CRISP methodology (Wirth & Hipp, 2000) reduces the probability of failure of an artificial intelligence project by ensuring that each important perspective is addressed during the process. It consists of six major steps:

1. Business Understanding
2. Data Understanding
3. Data Preparation
4. Modelling
5. Evaluation
6. Deployment

In this paper, the authors examine the first three steps, providing a valid framework for modelling and evaluation, which may lead to the solution deployment. Special focus is placed on examining the effects of these steps on the usability of artificial intelligence and its effects on business performance.

This research examines the processes and factors that significantly influence inventory planning within the supply chains of sensitive pharmaceutical products. Important factors include data on the customer, product, sales, orders, logistics, and deliveries (Mahya & Mafakheri, 2020; Nguyen, Lamouri, Pellerin, Tamayo, & Lekens, 2021) and data-related processes. Based on well-prepared input data, the researchers focus on the metrics and flows of forecasting and optimising the inventory of sensitive products in the pharmaceutical chain. Special emphasis has been placed of late on the use of artificial intelligence in forecasting models. In existing literature (Achamrah, Riane, & Limbourg, 2021; Hiassat, Diabat, & Rahwan, 2017), approaches for prediction are found using neural networks, machine learning, deep learning, etc.

The paper continues with background research on inventory forecasting processes, factors and metrics, where the complexity of the preparation of research input data and metrics for forecasting inventory movements in supply chains are highlighted in more detail. The third chapter describes a proposal for the concept of a forecasting model through input data proposals and associated metrics based on artificial intelligence methods. Finally, the effects on the operation of companies are examined as well as the indirect effects on society and the environment, especially in the case of the use of limited quantities of perishable ingredients and products.

2 Background

Factors influencing inventory forecasts have been addressed by many authors. They address data content in the first part and the processes and models of inventory forecasting in the second part.

2.1 Critical factors for inventory planning

When forecasting inventory, it is necessary to observe the slightly broader issue of planning the entire supply chain, which includes suppliers of raw materials, production sites, logistics and, finally, users. Instead of separate approaches and models of department management (sales, purchasing, logistics, finance, etc.), the strategy of directing the operation of the supply chain should be comprehensively controlled (Shapiro & Wagner, 2009; Hiassat, Diabat, & Rahwan, 2017).

A company's supply chain is thus subject to a wide range of factors and risks that need to be monitored to ensure efficient management of the company's operations. Risks of a systemic nature are difficult to predict and monitor, as the company has limited or no influence on them and it is difficult to detect them in time. These include environmental risks, uncertain product demand, supply disruptions, sudden changes in regulations across countries, legal and bureaucratic changes, catastrophic unforeseen events (for example, earthquakes, large-scale fires, disease epidemics/pandemics, wars, etc.), infrastructure disruptions, etc. (Baghalian, Rezapour, & Farahani, 2013). In the pharmaceutical industry, the primary production of an active substance is particularly demanding. Carrying out chemical processes often requires a certain time span. In addition, different phases of manufacturing are usually carried out in multiple locations, for instance, the location where active components are manufactured may be geographically distant to the secondary production and packaging of the product for shipment to the market, which prolongs the time and complexity of the product preparation process (Shah, 2004).

Non-system risks are easier to control and more tied to the operation of the company itself. These include the well-coordinated operation of the functions of the entire company (Baghalian, Rezapour, & Farahani, 2013). Based on the latter, companies strive to reduce operating costs per unit of product sold (Ouyang, Yeh, & Wu, 1996).

The physical and chemical data of the product determine the manufacturing and storing of products (Mahya & Mafakheri, 2020; Nguyen, Lamouri, Pellerin, Tamayo, & Lekens, 2021), These data can be accessed from the product specifications and by taking measurements, which contain relevant information on the product, quality, ingredients, shelf life, storage temperature conditions, etc.

The next data group is past performance data from a company's ERP system, which include data on sales history and demand for each product (Mahya & Mafakheri, 2020; Nguyen, Lamouri, Pellerin, Tamayo, & Lekens, 2021). Some authors also calculate the uncertainty of the quantity of urgent demand, fixed costs with orders and the average annual demand for the product (Meng, Guo, & Zhang, 2021; Ouyang, Yeh, & Wu, 1996).

The sales and production planning data are to be included in the model, i.e. short-term production plans and long-term plans for product demand or the so-called production plan, as well as the plan realisation data (Nguyen, Lamouri, Pellerin, Tamayo, & Lekens, 2021; Mahya & Mafakheri, 2020).

Inventory planning is additionally influenced by the resources available to plan the production process (Shapiro & Wagner, 2009; Nguyen, Lamouri, Pellerin, Tamayo, & Lekens, 2021). These include data on the capacity and limitations of the production process and assessments of the associated risks (Shapiro & Wagner, 2009).

Company-wide inventory and cost data serve as information for managing inventory levels, setting company policies and internal company information flow (Nguyen, Lamouri, Pellerin, Tamayo, & Lekens, 2021).

Logistical data on storage, transport and return flow must also be taken into account when planning an inventory. Serialisation data make it easier to monitor logistics flows and manage the quality levels of products entering the supply chain (Mahya & Mafakheri, 2020; Nguyen, Lamouri, Pellerin, Tamayo, & Lekens, 2021; Shapiro & Wagner, 2009). This technology enables monitoring of storage costs at the level of the product item throughout the entire lifetime up to the end users (Ouyang, Yeh, & Wu, 1996).

Supplier data and contracts between them are more difficult to access and thereby less frequently used in research (Nguyen, Lamouri, Pellerin, Tamayo, & Lekens, 2021; Mahya & Mafakheri, 2020).

Some researchers focus on customer data and activities of the latter. The latter can be obtained from web search cookies, phone calls, home and clinical use of prescriptions, etc. Acquiring this data can be ethically questionable and should comply with the international standards for personal data management (Shapiro & Wagner, 2009; Mahya & Mafakheri, 2020; Nguyen, Lamouri, Pellerin, Tamayo, & Lekens, 2021).

In part, it is possible to monitor the changing requirements of users and the efficiency of a company's capital usage (Achamrah, Riane, & Limbourg, 2021; Nguyen, Lamouri, Pellerin, Tamayo, & Lekens, 2021). An important factor is the monitoring of contracts between governments and producers within data on state reserves (Meng, Guo, & Zhang, 2021). Researchers also pay attention to environmental data as well as data on outbreaks of recurrent diseases, statistical information from population change databases and others (Nguyen, Lamouri, Pellerin, Tamayo, & Lekens, 2021).

With the ever faster operation of companies with short delivery times, key data on the preparation of active ingredients is required to determine the ability to deliver on time and avoid the cost of penalties and delays in the event of late or cancelled deliveries (Hiassat, Diabat, & Rahwan, 2017; Ouyang, Yeh, & Wu, 1996).

2.2 Inventory forecasting processes and models

Inventory forecasting processes can be defined as a function of the average product flow, to balance costs as efficiently as possible and the movement of storage capacity with an optimal inventory (Shapiro & Wagner, 2009). Market requirements are addressed by providing the shortest possible delivery times and the best possible adaptation to customers in a changing market to ensure the efficient operation of the company (Achamrah, Riane, & Limbourg, 2021).

A basic method for monitoring the level of inventory is the minimum-maximum method, where the critical limits of inventory products are determined. When the inventory of a particular product falls below the set limit, the order is executed up to the maximum capacity of the inventory (Shapiro & Wagner, 2009).

Some authors prefer to associate the optimisation of storage capacity with forecast sales models, such as ARIMA (Autoregressive Integrated Moving Average). Sales planning is the basis for optimising production, purchasing, logistics and efficient people management. Time series analysis and trend searches can lead to effective predictive models based on the detection of autocorrelations of integrated averages in data (Ramos, Santos, & Rebelo, 2015; Fattah, Ezzine, Aman, El Moussami, & Lachhab, 2018). The use of the DEA (Data Envelopment Analysis) method is often mentioned for analysing the performance scenarios of individual units with an emphasis on improving the input data for the supply chain results optimisation (Habibifar, Hamid, Bastan, & Azar, 2019).

One of the most challenging tasks for any industrial company with a large product mix is the creation of a robust production schedule to augment the manufacturing managers, thus enabling dynamic experimentation and validation of products, processes and system design and configuration. (Mourtzis, 2020) provides insights into the history and state of the art trends of manufacturing simulation support. (Kaylani & Atieh, 2016) propose a discrete event simulation approach. They evaluate the credibility of the generated schedule by measuring the utilisation of resources, identifying bottlenecks and throughput, and evaluating the impact of each item in the product mix on these performance measures.

Some companies use forecasting approaches in which they prioritise high-reward customers. This means that when entering requirements into the system, they reserve a certain part of the inventory for 'urgent' customers, which increases the 'total reward (Cheung, Ma, Simchi-Levi, & Wang, 2022). In this case, it is not only the realised price that is relevant but also the risk management for individual business scenarios (Baghalian, Rezapour, & Farahani, 2013).

In the state-of-the-art literature, researchers mention the method of genetic algorithms over the initial population of input data. In the first step, it is necessary to place the chromosomes, i.e. perform coding on the traceability of products from the manufacturer to the end-user. This is followed by initialisation, whereby the full capacity of the warehouse is utilised. In the third step, an optimisation simulation is performed with the help of linear programming, taking into account the market laws. The next phase is the change of priorities between products and customers, which leads to a circular loop of finding the optimal choice. The key is to evaluate the overall performance of care for the best possible use of a company's resources. Several selections are then made, whereby options with lower costs for the company are put in the foreground. The selected option is also checked later during the new generation of products (Achamrah, Riane, & Limbourg, 2021; Hiassat, Diabat, & Rahwan, 2017).

The trend in existing literature focuses on machine learning and, consequently, a subset of deep learning. The latter is useful when dealing with large volumes of complex data. It is used to identify matches within the given input data and is often used in combination with neural networks (Achamrah, Riane, & Limbourg, 2021).

The use of neural networks that mimic the properties of biological neurons in the nervous system during the analysis of input data is also becoming more common. It allows the approximation of complex relationships between input data using nonlinear functions. Some authors use it to capture the time series of several nonlinear variables (for example, in sales). The method is also effective for a small set of historical data, due to the rapid change of products while adapting to situations in the pharmaceutical market (Zedeh, Sepehri, & Ferveresh, 2014).

3 The model

In this research, the authors have examined the application of AI models in inventory planning. The first three steps of the CRISP methodology have been examined:

1. Business Understanding
2. Data Understanding
3. Data Preparation

At the current stage, a conceptual analysis will be applied, thus opening the door for a more detailed physical modelling and examination of the applied AI-based predictive models in a business case.

3.1 Business Understanding

Even though inventory planning can be regarded as an isolated business process that can be easily optimised, it is closely integrated with the sales predictions and optimised manufacturing processes on the one side and the supply chain on the other side, bundled together with the company's business goals and performance measurement. This research addresses multiple closely related business processes, sales prediction, manufacturing simulation and optimisation, and inventory planning. For the application of AI to provide the expected business effects, single processed processes need to be examined from the perspective of how to augment people in charge of planning and optimising the processes to clearly elaborate the pivot points in which they need additional support. In addition, it is also important to identify how to format it and, most importantly, how to upgrade communication and collaboration between these managers to enable them to cope with the dynamics of the environment and utilise the organisational and process limitation.

In inventory management, AI can help clarify inventory plans, thus improving direct communication with related business users: manufacturing managers on the one side and direct suppliers on the other. Even though the focus is on communication with the direct business nodes, the systemic goal is to improve communication in the whole supply chain: from understanding the customers' expectations, sales predictions and manufacturing plans on the sales side to a better understanding of the capacities and limitations on the procurement side of the supply chain.

3.2 Data Understanding

Based on the literature review from Chapter 2.1, the authors propose eight groups of input data. These are inventory, data on past sales, orders received, long term contracts, production facilities with processes and costs, production properties and components, occupancy of warehouse and logistics.

Inventory data should contain data on the state of inventory movement of an individual product in a certain previous period in the warehouse.

The next group is historical product sales data, which includes data on sales volume to each partner.

The third group collects sales plan data. Short-term plans can be obtained from corporate ERP systems, while long-term plans need to look at indicative sales plans in the future.

The fourth group of data are long term contracts, which cover regular customers with known quantities of materials.

The next two groups represent data on products that can be obtained from a company's ERP system or product specifications. The characteristics of production and possible incompatibilities of simultaneous production of products at the same production location are also important. Storage data are also important to ensure appropriate storage conditions.

It makes sense to obtain data on the occupancy of each part of the warehouse according to the classification of the product, i.e. by separating drug warehouses, room temperature warehouses and cold chain.

The last group includes logistical data on the mode of transport and the possibility of providing appropriate temperature conditions. It also makes sense to include the potential risks of damage or malfunction of products during product distribution.

Information about product release dates is also included. This group also covers the specifics of the plans in the ERP system. Restrictions on the packaging and registration of medicines and the possible need for quarantine when importing the product should be highlighted at this point, as well as cover for emergencies (fires, floods, periods of respiratory diseases, etc.) and consequent time fluctuations in sales of individual products.

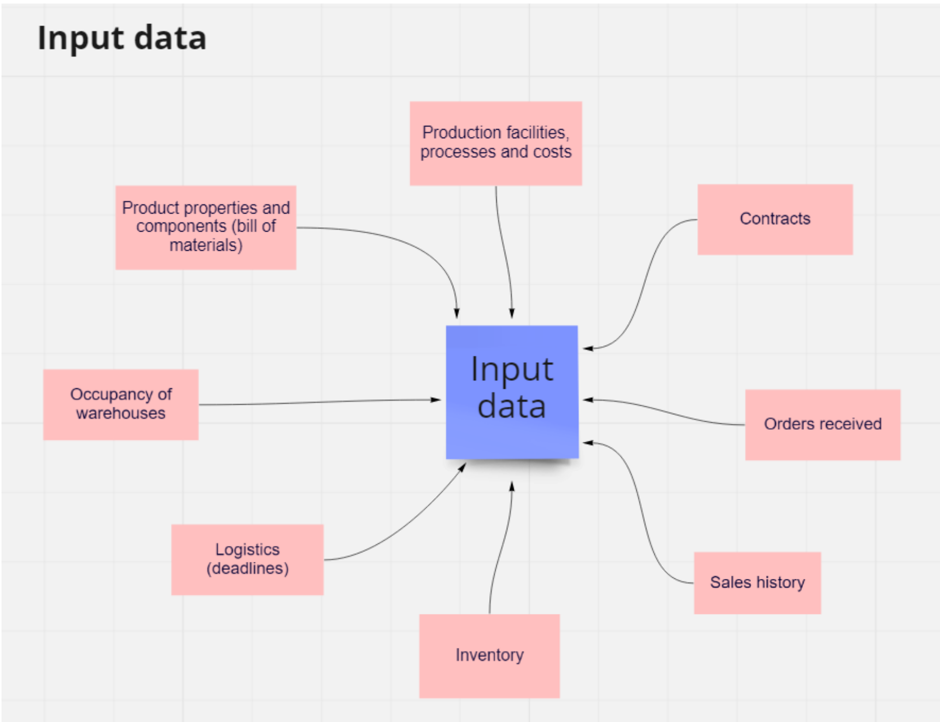

Figure 1: Proposed input data
Source: own.

3.3 Data Preparation model (the process)

Before preparing the forecast inventory model, a series of preparatory data models were prepared to dynamically link sales forecasts with production and storage capacity constraints and those related to the acquisition and gradual preparation of final product components.

The process model consists of three parts. The first part focuses on the forecast sales model with a combination of predicting time series using algorithms such as ARIMA (Zhang, 2003), upgraded by the long-term contractual orders and received/confirmed orders taking into account the current inventory in a company's logistics centre. Based on the sales forecast, the manufacturing processes can be simulated, taking into account production capacities, the understanding of processes and the costs stored in a company's ERP system (Klemm, 2021). The manufacturing simulation model is the basis for inventory planning (ibid.). Data are required on occupancy, types of warehouses, products from specifications, etc. The result of the raw material is active support in preparing procurement orders and managing manufacturing processes to fulfil users' requests.

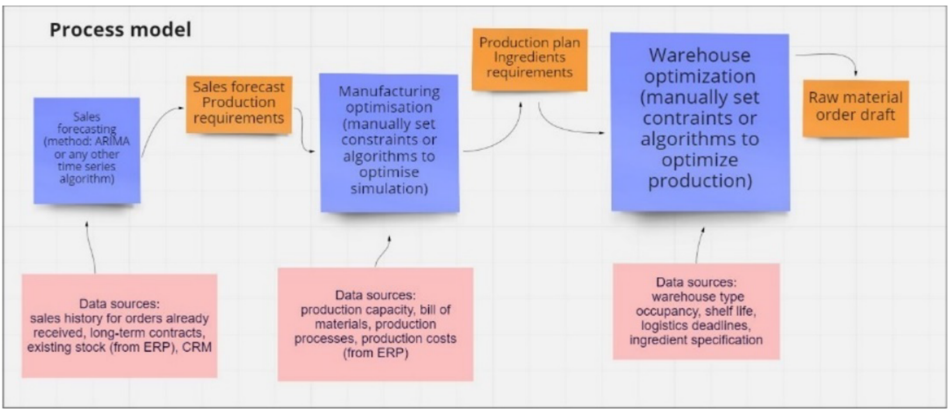

Figure 2: Proposed process model

Source: own.

4 Conclusion

The planning of supply chain storage capacities is a multifaceted problem combination of multiple interconnected segments in a dynamic environment. Business users need to coordinate and cooperate in sales forecasting, management simulation and procurement planning for optimal process execution. Particular attention should be paid to the data preparation phase, which is crucial for successful results in all stages of modelling. Data can largely be obtained from a company's ERP system and product specifications. Each segment needs to provide business users with the information required for communication with the other business users. Sales need to provide a trustworthy sales plan based on sales forecasting while manufacturing managers deliver requests for raw materials based on the production simulation to be processed by warehouse managers to issue the appropriate procurement orders. The final product of the modelling process – the procurement order of raw materials – is the foundation for directing the production and distribution of products process.

A good and well-coordinated supply chain will thus enable lean operations of the entire organisation, bring users a better supply of products, improve a company's financial results and reduce risk exposure. An improved planning process means that society will also benefit from higher-quality products. The products will therefore be exposed to reduced risk of failure in the period between production to reaching the end-user and will be delivered on time and without any damage. The environment and decision-makers will gain insight into the need to bring together key stakeholders in the event of global crises and the resulting disruption to the timely supply of adequate raw materials.

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