Complex KPIs versus the usual benchmarks

A case study on Svensk Dos order picking department

Shahin Armaki & Kawa Ahmad Mohammed

Degree project/Independent project • 15 credits
Swedish University of Agricultural Sciences, SLU
Faculty of Natural Resources and Agricultural Sciences/Department of Economics
Business and Economics – Sustainable Development
Degree project/SLU, Department of Economics, 1512 • ISSN 1401-4084
Uppsala 2023

Complex KPIs versus the usual benchmarks. A case study on Svensk Dos order picking department

Shahin Armaki & Kawa Ahmad Mohammed

Supervisor:	**Jens Rommel, Swedish University of Agricultural Sciences, Institute of Business Administration**
Examiner:	Richard Ferguson, Swedish University of Agricultural Sciences, Institute of Business Administration

Credits:	15 credits
Level:	First cycle, G2E
Course title:	Bachelor thesis in Business Administration
Course code:	EX0902
Programme/education:	Business and Economics – Sustainable Development
Course coordinating dept:	Department of Economics
Place of publication:	Uppsala
Year of publication:	2023
Copyright:	All featured images are used with permission from the copyright owner.
Title of series:	Degree project/SLU, Department of Economics
Part number:	1512
ISSN:	1401-4084

Keywords:	Warehousing, Regression, Analysis, Sweden, Pharmaceutical Industry

Swedish University of Agricultural Sciences
Faculty of Natural Resources and Agricultural Sciences
Department of Economics

Abstract

This thesis addresses the research gap of a limited discussion on how to establish targets and expectations for Key Performance Indicators (KPIs) related to order processing in warehouse settings. It emphasizes the scarcity of studies addressing this problem and the challenges faced by larger companies in monitoring their order processing performance without clear benchmarks.

Svensk Dos, a major pharmacy in Scandinavia, faces challenges in accurately measuring productivity at its medication roll packaging station. The current Key Performance Indicator (KPI) of 100 packed rolls per hour/operator may not be equitable and accurate due to external variables affecting performance, such as roll type and quantity per box. This raises concerns about the KPI's effectiveness in measuring productivity. Hence, this study develops complex KPIs based on cycle time per packed product and investigates the KPI’s impact on productivity and management. Data collection involves performance observations for a regression model that make up the complex KPI and qualitative interviews for understanding the use and application of the complex KPIs for Svensk Dos. The study contributes to warehouse KPI literature and provides recommendations for accurate productivity measurement in medication roll packaging stations. In conclusion, KPIs proved themselves to be great for staffing the order handling station in the case study. The use of complex KPIs is better than the use of simple averaging.

Table List

1. Introduction

The introductory chapter initiates with an exposition on the study's inception, followed by an in-depth examination of its objectives. This chapter comprehensively encompasses the study's notable theoretical and empirical contributions. Furthermore, it elucidates the precise boundaries of the research problem and provides a detailed overview of the thesis structure.

1. 1 Background

According to the World Economic Forum (2022), big data analytics, if integrated correctly, will become a key driver of innovation and growth in the manufacturing industry. As the industry increasingly adopts big-data analytics, it will enable businesses to optimize their operations, enhance their decision-making capabilities, and create new opportunities for value creation. Data and analytics will play a critical role in shaping the future of manufacturing. However, in a comprehensive survey of 1300 respondents conducted by the World Economic Forum (2021), found that only 39% of executives in different industries could successfully implement data-driven decision-making practices.

There are numerous challenges that businesses encounter when integrating data collection and data analytics into their enterprise. Some of the main problems that arise are the quality of the data, because 83% of companies believe that poor data quality has had an adverse effect on their operations (Experian, 2017). Only about 3% of businesses have proper data governance (TDAN, 2020) and there is a significant shortage of workers with the necessary skills to analyze big data (McKinsey, 2011; APEC, 2017). In other words, many of businesses find it difficult to collect appropriate data, to store data and to develop personnel to analyze data. This puts warehouse executives and managers in a peculiar position when it comes to goal-setting and decision making.

Supply chain and warehouse management has undergone a significant transformation due to technological advancements. Different methods have emerged as promising tools for enhancing efficiency and reducing costs (Rushton et al., 2017). The integration of technology has facilitated streamlined logistics operations, enhanced supply chain visibility and transparency, and improved the responsiveness of organizations to fluctuating customer demands (ibid). Emerging technologies such as big data analysis, artificial intelligence (AI), robotics and automation have the potential to transform logistics and warehouse management leading to a more efficient supply chain (DHL, 2021; Supply Chain Digital, 2021). Different methods can be used in inventory and demand management, to boost operational efficiency, enterprise resource planning and more (Throughput, 2021).

From an academic perspective, the field of supply- and warehouse management started to take shape in the 20th century with the development of industrial engineering and operations research (Carter et al., 2015). Frederick W. Taylor, renowned as the pioneer of scientific management, brought forth the idea of time-and-motion studies. The primary objective of this concept was to enhance the effectiveness of industrial processes. As a result, new tools and techniques developed for managing the procurement, production, and distribution of goods. This gave birth to logistic- and warehouse management systems and supply chain optimization models (ibid). Following Taylors footsteps, Peter Drucker (1954) developed different methods for businesses to measure quality and performance, while Deming (1986) developed Total Quality Management which highlights the need for continuous improvement and introduces the implementation of more complex statistical methods into warehousing. As computerized management systems became popular, businesses in the manufacturing industry increasingly adopted the use of Key Performance Indicators (KPI) (Staudt et al., 2015; Rushton et al., 2017).

KPIs are specific measurable values that track an organization's progress towards its goals, and KPIs are distinguished from other metrics by their direct alignment with these goals (Parmenter, 2015). Data analysis can be performed on different kinds of KPIs (Forbes, 2021). According to Nagorny et al. (2017) data analysis with KPIs in smart manufacturing has groundbreaking potential but there are several challenges that lie ahead and further research is needed on the topic. Managers and executives in manufacturing usually set goals for their KPI either by benchmarking, simple averaging or by the shareholders wishes (Kusrini et al. 2018; Chen et al. 2017). But is that the optimal way to set up goals?

The aim of this thesis is to contribute to this debate by means of a case study. We will analyze whether there are alternative ways to set up goals for a manufacturer, namely through the use of data analysis and complex KPIs.

1.2 Theoretical Problem

There is a substantial body of research exploring the identification of Key Performance Indicators (KPIs), their relative significance, and their optimal management within warehouse settings. Nonetheless, a research gap persists regarding how to establish targets and expectations for KPIs in relation to order processing within warehouses as there are only a few studies addressing this problem (Kusrini et al, 2018; Marziali et al, 2021; Shvets et al., 2014). This gap creates several challenges for larger companies that seek to monitor the performance of their order processing operations, yet these companies lack a clear sense of what constitutes realistic benchmarks in order processing.

1.3 Empirical Problem: Case Study *Svensk Dos*

Svensk Dos is one of Scandinavia's largest dose pharmacies, where dosage rolls of medicine are produced and shipped to different parts of the country. The packaging station for medication rolls is considered a crucial order handling station at *Svensk Dos*. However, the current KPI, which measures 100 packed rolls per hour/operator, may not be a “fair” KPI for operators due to the impact of underlying variables that affect performance for packing which are outside the control of the operators. These variables include the type of medicine roll which is being packed and how many rolls are being packed in the same box. Furthermore, the KPI that should be used for an order handling station is cycle time for one packed product (Kusrini et al., 2018) and not the total number of packed products by an operator. This raises questions about the effectiveness of the KPI in measuring the productivity of the medication roll packaging stations. Management's lack of understanding of how to use the correct KPI further complicates the issue. The empirical problem aims to explore how to create and integrate the best KPI tailored for a specific order handling station and to investigate the KPIs impact on productivity and management at a packing station.

Empirical data were collected through observations on performance which leads to the development of a new KPI. In addition, qualitative interviews with operators and management at *Svensk Dos* were conducted to gain further insight on whether the newly developed KPIs have had an effect on productivity and managemen. The study will also consider the impact of different types and numbers of rolls on productivity and evaluate the appropriateness of Kusrini et al.'s (2018) suggestion to measure cycle time per packed unit instead of the total number of packed rolls.

The findings of this study will contribute to the literature on warehouse KPIs (Kusrini et al., 2018; Marziali et al., 2021; Nagorny et al., 2017). Our assesment of the effectiveness of KPIs in measuring productivity can provide recommendations for the development of more accurate KPIs to measure the productivity of medication roll packaging stations.

1.4 Purpose

The purpose of this research is to investigate the effectiveness of complex key performance indicators compared to the commonly used benchmarks within warehouse operations. To establish a foundation for the research objectives, the following research questions will be addressed:

- How can KPI goals be constructed in a justifiable manner for order handling activities within a warehouse setting? (1)
- Are the identified KPI goals more effective than the different usual benchmarks used in warehouses? (2)

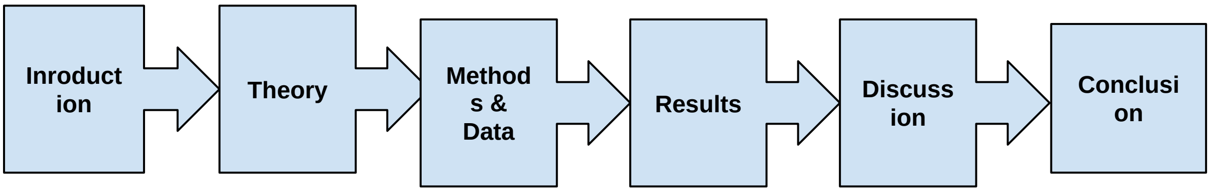
1.5 Boundaries

The scope of the study was restricted to *Svensk Dos*, one of Sweden's largest manufacturers in the pharmaceutical dosing industry, focusing specifically on their warehouse. Owing to the study's nature, the analysis is limited to one KPI that measures the cycle time involved in packing a single product at the most crucial station in the largest department of the warehouse. A sample of 500 observations was collected and divided among 18 workers to create complex KPIs based on underlying variables that affect cycle time. The selected variables were assumed to be the most critical factors for the analysis, based on the researchers' personal experience.

1.6 Disposition

The following section explains the structure of the thesis.

Figure 1. Explaining the structure of the thesis



Chapter 1: The introduction begins with providing a background to the topic. The problem discussion then leads to the research objective. The chapter also includes a description of the study's contributions and the limitations set by the authors.
Chapter 2: The theory chapter provides an overview of prior research. It then proceeds to define the concept of what a KPI is and elucidate the theories chosen for this study.
Chapter 3: In the methodology chapter, the authors outline their selection of method and provide details on the process of sample selection, data collection, and analysis. Subsequently, the discussion revolves around the credibility of the study.
Chapter 4: This chapter presents the findings through the utilization of tables and explanatory text. The calculations were performed using Excel and R Studio and the interview was conducted in a semi structural manner.
Chapter 5: In the discussion chapter, the results are subjected to analysis and discussed based on the previously presented theories. The intention of the discussion is to fulfill the objective of the study.
Chapter 6: Finally, we present a concise summary of their findings, conclude on their research questions, and offer recommendations for further research.

2. Theory

This chapter will feature a comprehensive literature review, encompassing pertinent theories. These theories will be presented to establish the foundation for the case study.

2.1 Literature review

The topic of warehouses and their performance assessment were long ignored by the literature (Johnson & McGinnis, 2011) although KPIs have frequently been used by business through the entire supply chain and in logistics management systems (Staudt et al., 2015). Shvets et al. (2014) define KPIs for warehouses as either strategic or normative. Where strategic KPIs are KPIs that do not have to be monitored in a short time frame. These are KPIs that contain a business' larger performance metrics like return on investment, market share, warehouse capacity and cost of storage. Normative KPIs on the other hand are performance indicators that are analyzed in a shorter time frame. These include KPIs for operational management like the cycle time of an operator's performance, machine downtime, staffing, overtime hours and picking accuracy. The goal of Normative KPIs is that they should be kept at a level that keeps the warehouse functional (ibid).

KPI are organization-specific (Awan et al, 2013). Warehouses put more focus on KPIs involving delivery reliability and customer satisfaction (ibid). Each activity in a warehouse has different kinds of KPIs. Five activities are generally done in most warehouses according to the Fraze model (Kusrini et al, 2018). These are Receiving (scheduling of trucks and unloading materials), Put away (Placing products in warehouse), Storage (moving material to the rightful place), Order picking (preparation of an order) and Shipping. According to Kusrini et al. (2018) each one of these activities have a main KPI and improvement in the warehouses can be made based on improving the main KPI in each activity.

Table 1. The most important KPI for each warehouse activity (Kusrini et al., 2018)

Activity	*KPI*
Receiving	Receive per man-hour
Put away	Cycle time
Storage utilization	% Location and cube occupied
Order picking	Cycle time
Shipping	Orders prepared for shipment per man-hour

Improvement can be defined and done in different ways. But benchmarking, simple averaging and setting goals based on the wishes of management are the usual ways (Kusrini et al. 2018; Chen et al. 2017). Chen et al. (2017) concludes that in order for KPIs to work successfully in warehouses, management should have a comprehensive KPI management system that incorporates the plan-do-check-action (PDCA) model. This would put an organization SMART and normative KPIs in an ever evolving state, continuously converging for the better over time. Another way to improve performance are complex KPIs (Shvets et al., 2014). A complex KPI is a KPI that takes account of the underlying variables that affect a certain KPI (ibid). A complex KPI for shipping could take account for variables such as, the number of available trucks and the level of skill the individuals who are driving those trucks have. The complex KPI would then be based on a model of these underlying variables.

Taking into account the underlying variables for KPIs leads to more advanced statistics. It has been noted that incorporating statistical methods, machine learning and artificial intelligence in the management systems of warehouses has a direct positive influence on performances (Angammana & Jayawardena, 2022; Shvets et al., 2014; Tokat et al., 2021). Specifically, on the KPIs stressed to be of importance by Kusrini et al., (2018)

In summary, there is an academic debate on what a KPI is and what type of KPIs perform best in a given context. There is also a smaller literature discussing on the use of specialized KPIs in warehouses. However, much less is known about model-based indicators and how to adjust them to specific needs in a given warehouse context. Setting goals and expectations in a warehouse is either done by benchmarking, simple averaging or by the wishes of management (Shvets et al., 2014). When one may ask the question where model-based indicators may improve the performances of a warehouse.

2.2 Theory

Data can be collected on a lot of things and measured in a lot of different ways within a business. The metrics for data are typically categorized into one of the following subgroups of business: Financial metrics, Customer metrics, Operational metrics, Sales metrics, Marketing metrics, Employee metrics and Environmental metrics (Ax et al. 2021). Everything that is traceable in a business can be defined as a metric. The metrics that are directly relevant to the business goals are called key performance indicators (KPI) (Parmenter, 2015). Therefore, all KPIs are metrics, but not all metrics are necessarily KPIs.

Different streams of the literature define subgroups of KPIs. According to Parmenter (2015) there are four main categories of KPIs: Performance, Process, Result and Driver. Performance KPIs are used to define, find and drive opportunities of improvement, Process KPIs are used to discover inefficiencies, Result KPIs are for evaluating a business overall strategy, and Driver KPIs are used to make conclusions about future performance. Parmenter (2015) also makes a distinction between KPIs and SMART KPIs where the latter is preferred because it illustrates the performance of a business in a simpler and more effective manner. A

SMART KPI should be Specific (to something, like a task), Measurable (quantifiable), Achievable (realistic based on capabilities and resources), Relevant (to the business goals) and Time bound (so progress can be defined). These are some of the general forms of KPIs.

In the context of warehouse operations, KPIs can be used to track and analyze key metrics, such as order fulfillment rates, inventory accuracy, and order cycle time. By collecting and analyzing data on KPI, businesses can gain a comprehensive understanding of their warehouse performance and identify areas for improvement (Johnsons & McGinnis, 2011).

Despite the potential benefits of KPIs and data analytics, many businesses still rely on manual methods of tracking and analyzing warehouse performance. This approach can be time-consuming, error-prone, and can lead to missed opportunities for improvement. As such, there is a clear need for businesses to adopt more advanced approaches to warehouse performance management (Forbes, 2022).

3. Methods and Data

In this section, a comprehensive methodological background is provided, encompassing a detailed description of the data utilized and the practical execution of the study. Following this, a meticulous examination of the study's reliability will be undertaken.

3.1 Overview

A mixed methods case study will be undertaken. The study will utilize a quantitative research method with a deductive approach to examine research question (1). The study assumes an ontological position that objective reality exists and can be estimated, and an epistemological standpoint that is positivistic, where learning is obtained through measuring an objective reality, which can be reliable and valid. To achieve this, the study will employ a regression analysis (Asteriou & Hall, 2016) that examines the performance of operators with cycle time as the dependent variable and the size and type of work as independent variables. Customized complex key performance indicators will be developed based on the specific work requirements to answer research question (1).

In contrast, research question (2) will be investigated using a qualitative research method with an inductive approach (Bryman & Bell, 2017). The study will collect empirical data through semi-structured interviews with management and individuals who have utilized the complex KPIs. The epistemological standpoint taken is the interpretive perspective, as the answer to research question (2) can be interpreted in various ways. The collected data will generate theory to address research question (2).

3.1 Selection of Warehouse

Svensk Dos is one of Sweden's largest dose pharmacies and has its warehouse in Uppsala, which produces medical dose rolls for the entire country (*Svensk Dos*, n.d.). The company's warehouse consists of three departments: Incoming goods, production, and picking & packing. Order handling takes place at a total of twelve stations across the two departments called production and picking & packing.

The objective of the model is to make precise predictions, while maintaining an acceptable degree of error, regarding the cycle time required for packing an order at a particular company's workstation. The aim is to evaluate whether the proposed model outperforms the industry benchmarks. Given that the focus of this investigation does not pertain to the overall cycle time across multiple warehouses with comparable workstations, it was deemed satisfactory to limit the study to a single warehouse for the purpose of this research.

3.2 Data

The data collected are mainly divided into one dependent variable, and several potential independent variables. The data are collected from one of the most important stations at *Svensk Dos*. The packing station is the last station in the production line and the main objective for an operator who is working there is to pack the product being produced into different sized boxes. There are eight workbenches for this particular station during the day shift, and fourteen workbenches during the night shift if needed.

3.2.1 Dependent variable

The dependent variable in this research is cycle time. It is considered as the most important KPI for this particular activity (Kusrini et al., 2018). The data is defined as, from the moment a worker takes on the task to the moment he or she's delivered the packed box to its designated place and walked back to his/hers workstation. This is measured in full minutes with fractions.

3.2.2 Independent variable

There are endless potential independent variables that could affect the cycle time. However the aim of the study is not to find the best model explaining cycle time, but the best model that could potentially be used by management in order to estimate cycle time. This eliminates independent variables that have a potential effect on the dependent variable but are too difficult to obtain. Variables like, workers exhaustion- , distraction, stress, etc. While accounting for relevant variables may alleviate omitted variable bias, variables such as stress or distraction are also endogenous and could be dependent variables themselves, calling into question assumptions of a causal identification strategy. Hence, we solely rely on exogenous variables and include only those that are relevant for management and the development of a parsimonious KPI.

Based on an overview of the company's stored data, two independent variables were found to be easily accessible and potentially explanatory.

3.2.2.1 Size

The quantity of dose rolls packed in each box may vary, thereby causing fluctuations in the corresponding cycle time. Specifically, as the operator packs a larger number of dose rolls, the cycle time tends to increase. This variable is determined by the number of dose rolls packed for a specific order.

3.2.2.2 Type

There are mainly two types of boxes being packed at the packing stations. “Regulars” and “Ombud”. The main difference between these two boxes is where they are being shipped. “Regulars” are being shipped to hospitals and retirement homes, i.e., places where a nurse can receive the box and delegate the dose rolls to the patients. These boxes are packed in a way where all dose rolls can be placed into one plastic bag and then later packed into the box. “Ombud” shipping’s are sent to private patients and each roll must be sealed in a separated black plastic bag, for privacy reasons. They may go down into the same box and can be sent to a place where the patients could come and pick them up, but they must be individually sealed. The different nature of these two types of packing methods affect cycle time. Therefore, type is defined as a categorical variable. Either the box is of “Regular” type or of an “Ombud” type.

3.3 Data and Sampling

The workstation being analyzed is in the Picking & Packing department which is the second largest department in the warehouse. Around 40 operators work there in two shifts. There is about a 4:1 distribution between full time employees and consultants on the floor. All the names of the employees were converted to numbers and a random generator randomly selected eighteen out of the forty numbers represented by the employees. The researchers made sure that there was a representative distribution between full time employees and consultants in the sample. There were a selected few that were eliminated from the sample because they exclusively work on other stations.

The company's database employs a software program named Candos to capture and register the operator's work performance. Notably, all data points were obtained exclusively through Candos. Even though the operators knew data was being recorded for research, to minimize the risk of bias, the researchers did not disclose the specific time or performance under observation to the operators. The data collection process spanned a year, thereby mitigating the influence of seasonality or temporal factors on the data.

A total of 500 observations were collected. The collected data was equally distributed among the operators so that one or a few individuals' results would not disproportionately affect the results. The observations were categorized based on the type and the size of the box. A sample size of 500 allows us to detect even relatively small differences in the independent variable at reasonable levels of statistical power (80%), hence limiting the possibility of a type II error (false negatives, i.e., not finding an effect that might be present in the population).

Table 2. The range of dose rolls in each box size category.

Box size	*Number of dose rolls*
Small	0 - 3
Medium	4 - 14
Large	15 - 32
Extra Large	32 <

The researchers categorized the data based on the sizes of boxes that were being packed in at the examined station. Based on information from management, the distribution of different sized boxes being packed every day was 15%, 25%, 35%, and 25% for small, medium, large, and extra-large sizes, respectively. The goal was to get the collected data to somewhat mirror this distribution. So, one type of packing size would not be disproportionately represented in the data.

Table 3. The distribution of the collected data based on the size of the box.

	Small	*Medium*	*Large*	*Extra Large*	*Total*
Ordinary	66	85	80	44	275
Ombud	15	49	84	77	225
Total	81	134	164	121	500
%	16	26.8	32.8	24.2	100

The reason for the discrepancy between small Ombud and small Ordinary is due to the fact that there are very few small Ombud being shipped by the company. Observations were more concentrated on large and extra-large “Ombud” since they exhibit a greater degree of variability of cycle time. Also, because they exhibit a larger range between the amount of rolls in the boxes.

3.4 Regression Analysis

There are many different data analysis methods, but due to the exploratory nature of this research, a linear regression model was deemed as sufficient. A simple regression model analyzes the relationship between a dependent variable and one independent variable (Wackerly et al., 2008). A multiple linear regression model analyzes the relationship between a dependent variable and multiple independent variables. The purpose of such analysis is to create a mathematical model that can, under some assumptions, also predict the dependent variable based on the independent variables.

There are a few criteria that should be met in order for a regression model to be deemed fairly representative and usable (i.e., to meet the so-called BLUE criteria under the Gauss-Markov theorem). In addition the data should be a random sample, and the sample size should be large enough to detect effects of interest.

3.4.1 Bias

The problem with a bias dataset for a regression model is that there is a considerable difference between the expected value of the model's forecasts and the actual value of the dependent variable. Predictions on the dependent variable in a biased model either lead to an underestimation or to an overestimation. There are different causes for bias in a regression model.

One of the potential reasons is when the sample of the dataset doesn't reflect the true population that is being analyzed (i.e., there is a selection effect). Another reason is when a linear regression model is being fitted to a non-linear relationship without taking the proper functional form into account. Measurement error is also a problem that could lead to a bias model. That is when the measurements of the collected data is either skewed or inaccurate in some other way. All of this may lead to biased parameters estimates which in turn leads to inaccurate predictions.

3.4.3 F-Test and T-Test

The F-statistic serves as a tool in regression analysis to examine the global significance of a model by testing the null hypothesis that all regression coefficients, except the intercept, are zero (Körner & Wahlgren, 2002). The F-statistic quantifies the ratio of the variance that is explained by the model to the unexplained variance, and it assesses whether the model can account for a meaningful proportion of the variation in the dependent variable (ibid). A large F-statistic coupled with a small associated p-value suggests that the model fits the data well and that the independent variables make a substantial contribution to explaining the dependent variable (ibid).

In a regression model, a t-test is applied to evaluate the probability of the data under the null hypothesis (hence it is a conditional probability). A small p-value points towards incompatibility of the data with the null hypothesis.

3.4.4 Regression Model

To analyze the relationship between the dependent variable and the two chosen independent variables a regression model is constructed. A multiple regression model is defined as follow (Wackerly et al., 2008):

$$y_i \;=\; \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \ldots + \beta_p x_{p,i} + \varepsilon_i \qquad (1)$$

Table 4. Table explaining each regression symbol (Wackerly et al., 2008)

y_i	denotes the recorded values of the dependent variable. In the case at hand this is the cycle time for packing a box.
x_i	denotes the recorded values of the independent variable, the size and type of box.
β_0	is the intercept of the model
β_p	represent the regression coefficients for the independent variables
ε_i	is the error term for the model which is assumed to be identically and independently distributed.

Some of the assumptions of a multiple regression model are the fact that the expected value of the error term is zero and it is also assumed that there is a linear relationship between the dependent variable and the independent variable. (Wackerly et al., 2008).

The significance level represents the probability of the data under the null hypothesis. Hence, a low p-value indicates incompatibility of the data with the null which may point towards the fact that the relationship between the dependent variable and independent variable is not due to chance. To assess the statistical significance of a test, a p-value of less than 5% is typically selected (Wackerly et al., 2008). Consequently, a p-value of 5% was adopted in this study. This means that there is a 5% risk for a type-I error. The entire battery of tests and analyses was carried out in R Studio and Excel.

3.5 Reliability

According to Bryman and Bell (2017), reliability pertains to the consistency of measurements and the stability of findings. Specifically, it denotes the extent to which the results of an analysis would remain unchanged if the research were to be replicated. There are different forms of reliability, mainly *stability* and *inter-rater reliability* (Bryman & Bell, 2017).

Stability reliability, also known as test-retest reliability, refers to the degree of consistency exhibited by measuring instruments over time. To evaluate stability, a particular measure or test is administered to the same group of subjects on two or more occasions, typically with a significant time gap between each administration. When sampling in this research every subject had multiple observations within the range of the same box size.

3.6 Validity

Validity refers to the extent to which a causal relationship can be reasonably inferred (Bryman & Bell, 2017). In a multivariate analysis, it is crucial to ascertain that the observed relationship between dependent and independent variables are authentic and not influenced by a third variable. To eliminate the possibility of spurious relationships, control variables are incorporated into the regression analysis. For example, in this study, the relationship that cycle time has with size and type of job is evaluated, while controlling for who the worker is.

To determine the reliability of the findings and establish which relationships are statistically significant, a significance level is calculated (Bryman & Bell, 2017). This helps to reduce the risk of falsely assuming a connection and improve the validity of the analysis. A significance level of 5% is generally deemed acceptable by researchers, meaning that any observed relationship that cycle time has with size and type of work must achieve a statistical significance level of 5% to be considered genuine.

3.6 The Qualitative Data

According to Bryman and Bell (2017), the interpretivist paradigm is concerned with analyzing and interpreting individuals and social institutions. The primary justification for adopting this approach is rooted in the belief that employing scientific methods to investigate social dimensions is not suitable.

To investigate the research question (2), a qualitative research methodology with an inductive approach has been adopted. The study has been delimited to conduct a comprehensive examination of whether the newly constructed complex KPIs are more beneficial compared to the methods previously employed at *Svensk Dos*. This examination has been carried out through the implementation of a case study design.

Empirical data are gathered through the utilization of semi-structured interviews conducted with Victor Lindström, Operations Manager, and Ghiyath Aljichi, team leader, both of whom are affiliated with *Svensk Dos*. By conducting interviews with these people, the research project aims to gain two distinct perspectives regarding the use and implementation of complex KPIs at *Svensk Dos*.

4. Results

In this chapter, the outcomes of calculations carried out using R-studio and Excel will be presented. Tables will be employed to effectively display these results, aligning with the study's specific objectives.

4.1 Regression model

The cycle time required for packing a parcel served as the dependent variable, while the size, quantity of dosage rolls in a parcel, and type of order were considered as independent variables. The two different order types were “regulars” and “ombud”. Each order type has its own unique packing method which influences packing style. Cycle time is handled as a real number, size is discrete, and type is categorical. The categorical nature of the “ombud” and “regulars” lead to the separation of the dataset based on type. That is, two different simple regression models were constructed with size as the only independent variable. One with the dataset of “ombud” and one with the dataset of “regulars”

4.1.1 Regulars

This is the dataset of the cycle time of packing a parcel where the type variable is set as “regular”.

Table 5. Regression statistics for the model with “regular” as type.

R^2	*Adjusted R^2*	*F-statistic*	*Significance F*
0.8247	0.8240	870.3	<0.001

There are strong indications that the model is useful. The F-statistics evaluate the overall significance of the model. With a very small p-value it is safe to assume that the model as a whole is useful in analyzing the variability of the dependent variable. The R^2 and the adjusted R^2 value is around 82% indicating that 82% of the variability of cycle time for packing a “regular” parcel could be explained with the size variable which is the amount of dosage rolls packed. This only applies to parcels of the “regular” type.

Table 6. Regression coefficients for the model with "regular" as type.

	Coefficient estimate	*Standard error*	*P-value*
Intercept, (β_0)	0.8172	0.0722	<0.001
Rolls, (β_1)	0.0953	0.0032	<0.001

The intercept of the model is the value of the estimated cycle time given that the independent variable, size, is set to zero. This could be interpreted as the time it takes to build the parcel, waiting for the papers to be printed and delivering the parcel to its designated pallet - things that are unaffected by the number of packed dosage rolls. The value for the intercept is around 0.81 minutes which is about 49 seconds. There is a standard error of about 0.07 minutes which is around 4.3 seconds. The p-value for the intercept is <0.001 which indicates that the coefficient is statistically significant.

The coefficient estimate for rolls is around 0.09 minutes with a standard error of about 0.003 minutes. The interpretation is that for each regular dosage roll being packed, the cycle time increases by approximately 5.7 seconds (with a standard error of 0.19 seconds). The p-value of the estimate is <0.001, meaning that there is strong inconsistency of the data with the null hypothesis.

Table 7. 95 % confidence interval for the model with "regular" as type.

Cycle time (minutes)	*Model*
Upper limit	$0.9616 + 0.1017*(X_R)$
Expected	$0.8172 + 0.0953*(X_R)$
Lower limit	$0.6728 + 0.0899*(X_R)$

This leaves us with three different models. One with the upper bound of the confidence interval, one of what is expected and one of the lower bound of the confidence interval. The upper limit could be used to make conservative predictions while the lower limit could be used to make optimistic predictions on performance.

4.1.2 Ombud

This is the dataset of the cycle time of packing a parcel where the type variable is set as "Ombud".

Table 8. Regression statistics for the model with "Ombud" as type.

R^2	*Adjusted R^2*	*F-statistic*	*Significance F*
0.7305	0.7282	311.8	<0.001

The F-statistics assess the overall significance of the model, and with a very low p-value of <0.001, we can confidently say that the model explains some of the variability in the dependent variable. The R-squared and adjusted R-squared values are approximately 72%, indicating that about 72% of the variation in the time it takes to pack an "ombud" parcel can be explained by the size variable, specifically the quantity of dosage rolls packed.

Table 9. Regression coefficients for the model with "regular" as type.

	Coefficient	*Standard error*	*P-value*
Intercept, (β_0)	0.4381	0.7259	0.54
Rolls, (β_1)	0.6219	0.0352	<0.001

The intercept in the model represents the estimated cycle time when setting the amount of packed dosage rolls as zero. Similarly, to the "regular" version it can be interpreted as the different things an operator has to do when packing a parcel that are not affected by the amount of dosage rolls being packed. The intercept value is approximately 0.43 minutes, equivalent to around 26 seconds. The intercept has a standard error of roughly 0.72 minutes, corresponding to approximately 43 seconds. The p-value for the intercept is 0.54, indicating that it's not of statistical significance. This means that the intercept does not differ from zero when the independent variable is set to zero.

However, the coefficient for the size variable is significant with a p-value of <0.001. We can reject the null hypothesis and assume that the amount of dosage rolls has an effect on the dependent variable, cycle time. We can interpret this as for each added "ombud" dosage roll the cycle time increases with around 0.62 minutes or 37.3 seconds. The coefficient also has a standard error of 0.035 minutes or about 2.1 seconds.

Table 10. 95% confidence interval for the model with "ombud" as type.

Cycle time (minutes)	*Model*
Upper limit	0.4381 + 0.69239*(X_O)
Expected	0.4381 + 0.62195*(X_O)
Lower limit	0.4381 + 0.55151*(X_O)

The confidence interval leaves us with three distinct models: one based on the upper bound of the confidence interval, one reflecting the expected values, and another derived from the lower bound of the confidence interval. This range of models allows for a comprehensive exploration of potential outcomes, accommodating both cautious and optimistic perspectives.

4.2 Interview

This is a summary of two separate interviews that were held with Victor Lindström, the operational manager of *Svensk Dos* and Ghiyath Aljichi, the team leader on the floor. They were both conducted in a semi-structured format. By the time of the interview the KPI models had been implemented in *Svensk Dos* management system for about six months

Background

Svensk Dos has used different ways of setting up goals through the years since they have not had the right system for tracking performances. In the earlier days when they were a smaller company they found it easier to track performances since there weren't too many operators to keep track of. Management had closer relation with the operators so investing money and time on KPIs for performances felt silly.

But the company has grown a lot since then. There used to be three operators in the packing department. Today there's about forty. When they won the Skåne contract production more than doubled in size leading to a lot of change. That's when they started using KPIs for the first time in the packing department.

KPIs

Management didn't have any information on how the competition was handling their KPIs for this particular station, so benchmarking was out of the question. They did some simple averaging instead. By dividing the total amount of dosage rolls that were being produced per day by the number of working stations that they had. Since there were two shifts working eight hours a day on eight working stations and a total of 12500 dosage rolls that needed to be packed. They simply divided 12500 dosage rolls by the number of hours by the two shifts for the two stations and rounded the number up to about 100. So packing 100 dosage rolls an hour became what was expected of each worker an hour. That is 800 dosage rolls packed a day. They did this because it was the only way they could define clear guidelines for what to expect from a quantitative performance perspective and it's the only KPI they have ever used for the station.

Problem with KPIs

These KPIs lead to some notable problems in the department. The priority list for what should be packed first are the following: emergency parcels (the same as a "regular" parcel with one dosage roll), "ombud" parcels and "regular" parcels in that order. The problem is that everyone knows that packing "ombud" takes way longer than "regulars". In order to increase their statistics, a lot of operators preferred to pack "regulars" before "ombud" even though "regulars" were not prioritized. So, by the end of the last shift there tended to be more "ombud" left then what it was before the use of these KPIs. Missing what's prioritized could lead to fines and even loss of contract for the company. Realizing their mistake management made it clear that the KPIs are meant as guidelines and that it was okay for the *operators to not meet the criteria and packing what's prioritized first is more important. So the KPIs where there, but not taken as seriously.*

The new KPIs

The constructed KPIs were deemed usable by management and they were used in different ways for different purposes. Since they had the data for everything that's being produced before it came to the station in an excel file, integrating the models and being able to use them in an effective manner was relatively easy. The data for the two independent variables have been stored in the excel file since before. The models were integrated into new columns which calculated the KPIs.

The KPI models were used to determine how management should staff the dosage rolls packing stations. Over the past year Svensk Dos lost a contract and needed to cut back on some staff. The models were directly used to determine how they should restaff and the calculations used with the KPI models were used as a basis by management when arguing with the parent company for how many operators should be kept.

The KPI models also gave management a way to quantify and determine efficiency. This has been a problem Svensk Dos have had for a long time. Historically management has leaned on the team leader's subjective judgment on how effective an operator is. These KPI models provided an objective way to determine efficiency. The cycle time of each task that were being done by an operator has always been collected in their newer data system. But judging performances is useless unless one has clear and well defined expectations. The KPI models provided just that. So the difference between actual performances and expected performances could be used to determine efficiency in an objective manner. This could be used as more concrete guidelines to determine who gets permanent employment and who should get a higher raise.

Problem with new KPIs

The problem with the models is the fact that they assume that all of the work is out and waiting to be done. The packing station is the last station in a long production line. There are about a dozen stations that a batch of dosage rolls have to go through before ending up at the packing stations. So, when a batch ends up at the packing station is very hard to determine. They just know that if everything goes as planned every batch will end up at the packing station by the end of the day. But the models don't take this to account. The models assume that all of the batches are waiting to be packed. So one cannot blindly trust the models.

A potential solution for this would be to create similar KPIs for every station in the production line. That would be optimal. This way management could determine when a batch will be at what station. This is something that Svensk Dos has struggled with since its inception. One could manage the production line more effectively with such KPIs.

5. Discussion

The analysis of results in this chapter is grounded in the theoretical framework and assumptions put forth by the authors. Furthermore, this section will explore the contributions and limitations of the study, while also examining its overall impact and encountered challenges.

The aim of this study is to examine the efficacy of KPIs in contrast to various widely employed benchmarks in the context of warehouse operations. In order to establish a basis for the research objectives, the following research inquiries were as addressed:

- How can KPIs be constructed in a justifiable manner for order handling activities within a warehouse setting? (1)
- Are the identified KPI goals more effective than the different usual benchmarks used in warehouses? (2)

5.1 Constructing justifiable KPIs

There are many different ways KPIs could be constructed for an order handling station at a warehouse. The problem is whether they are usable and justifiable. According to Kusrini et al. (2018) the most important KPI for an order handling station is cycle time. This was one of Svensk Dos biggest problems when using KPIs historically. Instead of cycle time as KPI they used a simple average of a day's work divided by the number of working stations over two shifts. This didn't take account for the fact that there are different types of work ("ombud" and "regulars") being conducted on the same station. Type had a notable effect on how long it took to pack a parcel. As indicated in Table 11, our model predicts that, depending on the type and dosage rolls, handling a package can take less than two minutes (for five dosage rolls in "regular"), but it is also not unusual that it can take more than 20 minutes (for 50 dosage rolls in "Ombud").

Table 11. KPIs predicted with the estimated models in minutes.

Dosage Rolls	*Regular (minutes)*	*Ombud (minutes)*
5	1.3	3.5
10	1.8	6.6
20	2.7	12.9
30	3.7	19.1
50	5.6	25.3

Given this large range in cycle time, it is easy to see that a simple indicator may not sufficiently capture strong external drivers of cycle time. It takes about 6.5 times longer to pack an “ombud” dosage roll compared to a “regular” dosage roll when ignoring the constant. This is also the reason why operators preferred to pack “regulars” over “ombud”, potentially leading to delayed deliveries and lower customer satisfaction.

When studying table 11 we can also conclude that management grossly underestimated productivity with their simple averaging method. The old KPI for an order handling station was 100 packed rolls per hour by an operator. This could be done in different ways in less than an hour.

Starting by only calculating “regulars” since that was what the operators preferred to do because of the old KPIs. Five batches of twenty “regular” dosage rolls are expected to take about 13.5 minutes. The same work should take about 15 minutes when using the conservative model. There are many different combinations and permutations of how one could pack 100 dosage rolls but none will take longer than 30 minutes if the operator is packing batches of at least five “regular” dosage rolls. This means that an operator that is only packing “regulars” should be expected to pack at least twice as much, by conservative estimates, as the 800 dosage rolls per day which was the old KPI.

Packing five “ombud” batches of twenty dosage rolls is expected to take about an hour and five minutes. An hour and eleven minutes using the conservative model. Twenty batches of five rolls take about an hour and ten minutes and two batches of fifty rolls take about fifty minutes. So maybe 100 rolls an hour was a decent KPI when only packing “ombud”. The problem is that the clear majority of a full day's work is made out of “regulars”.

This highlights one of *Svensk Dos’* main problems. Due to the discrepancy of cycle time based on the type, a lot of “ombud” batches were held off by the morning shift where a lot of operators opted to pack “regulars”. This created problems for the night shift who had a strict deadline but a lot more “ombuds” to pack.

The KPIs that are used for improving an order handling station are benchmarking, simple averaging and the wishes of management (Kusrini et al., 2018; Chen et al., 2017). *Svensk Dos* did not have information on how competitors were performing at KPIs for the packing ordering station so they could not benchmark against them. Instead, they used the simple averaging method, but as we have argued this may have been a mistake, as cycle time should be the main KPI for an order handling station (Kusrini et al., 2018). The effect of this was, that *Svensk Dos* grossly underestimated workers potential for the majority of a day's work and at the same time operators started prioritizing “regulars” over “ombud” when it should be the other way around. This also highlights the importance of using an adequate -KPI as, using an inadequate KPI can have a negative effect.

The solution to this problem is to use cycle time as KPI and to account for the underlying variables which affects cycle time. The only way to account for the underlying variables is through the use of complex KPIs. Complex KPIs are used to improve KPIs for order handling stations in warehouses (Shvets et al., 2014). This study indicates that as well. There are studies that indicate that the use of statistical methods in management systems of warehouses had a positive effect on performance (Angammana & Jayawardena, 2022; Shvets et al., 2014; Tokat et al., 2021). The same can be said about this study, since management used the complex KPIs as basis of argument for how many operators they needed when negotiating with the parent company after loss of a contract.

According to Chen et al. (2017) successful KPIs should have a comprehensive management system which incorporates the PDCA model in order to constantly evolve. This could be done with these complex KPIs. One could simply add new observations on a regular basis and redo the model. This would put the model in an ever evolving state and it would reflect the expected performances by the operators better over time.

5.2 Complex KPIs vs the old KPIs

The previously used KPIs were deemed useless since they had the opposite effect of what they were meant to achieve. Because of that they were quickly scrapped. Benchmarking, simple averaging and setting goals based on the wishes of management are the usual ways to set goals (Kusrini et al. 2018; Chen et al. 2017) and therefore a way to set up KPIs.

It is hard to benchmark when you do not have anything to compare yourself to. Management did not have information on overall industry metrics, and that is why they could not benchmark. Because of this fact, the study lacks sufficient evidence to ascertain whether the developed complex KPIs outperformed the use of competition-based benchmarks. That is why we are not able to conclude whether the constructed complex KPIs were better than industry benchmarks.

This study indicates that in this specific situation complex KPIs may be more usable than simple averaging. Because of the significant effect that the type of dosage roll has on cycle time. However, one must note that complex KPIs are averages too, only averages that take account for underlying variables. This is just a cultivation of what has been stated in previous studies.

As stated by Victor Lindström, one cannot blindly trust the complex KPIs, since they assume that all of the batches making a day's work are out and waiting to be packed. Since the packing station is the last station of a long production line, management never knows for sure when a batch will end up at the packing station ready to be packed. If management would blindly trust the models during a slow day from the previous stations, they could end up understaffing.

A potential solution to this according to Victor Lindström would be to create similar complex KPIs for all of the previous stations too. This would give management foresight during slow days and they could calculate how potential hangups and delays in the production line could affect other parts of the production line. Such information would be immensely helpful when staffing part time workers. If a hangup would occur in the earlier stages of production one could use a combination of all the KPIs for all of the stations to calculate how many part time workers that could be called in as extra help with precision.

5.3 Method criticism

Since the study is designed as a case study, even if the conclusion is that the newly developed complex KPIs are more effective than the traditional benchmarks, the findings should not be overgeneralized beyond the specific context of the research.

It is worth noting that certain independent variables, such as the number of printed papers included with the dose rolls, conversations among operators during work, time of the day, or even individual characteristics, and whether the operators are sitting while working could not be monitored. These factors are difficult to monitor from a managerial perspective, which means they could not be incorporated into our model. However, it is important to acknowledge that these variables still have an impact on the dependent variable. On the other hand, having a benchmark that is based on too many personal characteristics could also backfire, as workers may feel too closely monitored and controlled, therewith compromising motivation and work satisfaction. Therefore, and to avoid endogeneity, our model was based on exogenous characteristics of the package, rather than personal characteristics of the work staff.

It is also worth noting that each observation was collected through a computer system. The researchers never saw how the operators were working when collecting data on performances. This means that observations used in the model may include observations where operators were not working according to company routines.

6. Conclusion

This thesis explored a research gap concerning the establishment of targets and expectations for Key Performance Indicators (KPIs) in the context of order processing within warehouse operations. This research gap is evident due to the limited number of studies addressing the specific problem (Kusrini et al., 2018; Marziali et al., 2021; Shvets et al., 2014). Consequently, larger companies face a series of challenges when attempting to monitor the performance of their order processing operations, as they lack a comprehensive understanding of realistic benchmarks in this domain.

The primary objective of this research was to examine the efficacy of complex key performance indicators (KPIs) in comparison to commonly utilized benchmarks in the context of warehouse ordering operations. To establish a solid groundwork for the research, two main research questions were explored. How can optimal KPIs be constructed? Are the constructed KPIs better than what companies usually use?

One way to construct optimal KPIs for a warehouse ordering handling operation is through the use of complex KPIs. In this context complex KPIs are KPIs that take account of the underlying variables affecting the KPI. The ordering handling operation in this research was one of the packing stations at *Svensk Dos*. The main KPI for an order handling operation should be cycle time (Kusrini et al., 2018) which this research supports. Through the use of a regression analysis with cycle time as the dependent variable and the type of the task, and the size of the task as independent variables, complex KPIs were created to calculate the expected cycle time for each task which. That way each task has it's own KPI. Performances could be deemed as productive or non-productive from a more objective perspective by comparing an actual performance to the KPI. If the cycle time of packing a parcel took less time than what the KPI estimated, the performance would be deemed as productive. The opposite applies if a performance took longer than the estimated KPI.

The constructed KPIs were better than the ones *Svensk Dos* used before. The company used a simple averaging method by dividing a full day of work by each station over two shifts. This led to some notable problems which led the company to stop using KPIs for that order handling station. Until they received the constructed complex KPIs which were seamlessly integrated into management's excel system. With these KPIs management were able to determine how they should staff both in the short term and in the long term. The KPIs were used as basis when arguing with the parent company over how many operators should stay when the company went through a rough patch after a loss of contract. The constructed KPIs were better than what the company used to use in every way. But it wasn't perfect. The KPIs assume that all the tasks are ready to be handled.

Future research

Further research could be done by creating complex KPIs for an entire production line. This way one could determine how variations at one station could affect variations at another station and so on. Something like that would be a immensely powerful tool for management at a warehouse. It would also be worth wile to extend this research to other industries and cultural context and to assess the potential of including more characteristics of the work process, such as the work environment.

References

Angammana, J., & Jayawardena, A. (2022). Influence of artificial intelligence on warehouse performance: The case study of the Colombo area, Sri Lanka. Journal of Sustainable Development of Transport and Logistics, 7(2), 80-110. https://doi.org/10.14254/jsdtl.2022.7-2.6

APEC. (2017). Data Science and Analytics Skills Shortage. Asia-Pacific Economic Cooperation. Singapore.

Asteriou, D., & Hall, S. (2016). Applied Econometrics (3rd ed.). Liber. Stockholm.

Awan, H., Bhatti, I., & Razaq, Z. (2013). The key performance indicators (KPIs) and their impact on overall organizational performance. Quality & Quantity. https://doi.org/10.1007/s11135-013-9945-y

Ax, C., Kullvén, H., & Johansson, C. (2021). Den nya ekonomistyrningen. Liber AB. Malmö.

Bryman, A., & Bell, E. (2017). Företagsekonomiska forskningsområden (3rd ed.). Liber AB. Stockholm.

Carter, C. R., Rogers, D. S., & Choi, T. Y. (2015). Toward the Theory of the Supply Chain. Journal of Supply Chain Management, 51(2), 89-97. https://doi.org/10.1111/jscm.12073

Chen, P., Huang, C., Yu, C., & Hung, C. C. (2017). The examination of key performance indicators of warehouse operation systems based on detailed case studies. Information & Optimization Sciences, 38(2), 367-389.

Deming, W. E. (1986). Out of the crisis: Quality, productivity and competitive position. MIT Press. Massachusetts.

DHL. (2021). Logistics Trend Radar (5th edition). Retrieved from https://www.dhl.com/content/dam/dhl/global/core/documents/pdf/glo-core-logistics-trend-radar-5thedition.pdf

Drucker, P. F. (1954). The Practice of Management. Harper & Row Publishers. New York.

Experian. (2017). The 2017 global data management benchmark report. Experian Data Quality. Boston. Retrieved from https://www.experian.com.my/wp-content/uploads/2017/12/2017-global-data-management-benchmark-report.pdf

Forbes Technology Council. (2021, November 22). Key Performance Indicators (KPIs): The Lynchpin in Enterprise Data Analytics. Forbes. Retrieved April 24, 2023, https://www.forbes.com/sites/forbestechcouncil/2021/11/22/key-performance-indicators-kpis-the-lynchpin-in-enterprise-data-analytics/?sh=7490bbdc7704

Forbes Technology Council. (2022, September 27). Building a KPI mindset for growth. Forbes. Retrieved May 03, 2023, https://www.forbes.com/sites/robertsher/2022/09/27/building-a-kpi-mindset-for-growth/?sh=1ea6530255f7

Johnsons, A., & McGinnis, L. (2011). Performance measurement in the warehousing industry. IIE Transactions, 43, 220-230. https://doi.org/10.1080/0740817X.2010.491497

Kusrini, E., Novendri, F., & Helia V. N. (2018). Determining key performance indicators for warehouse performance measurement – a case study in construction materials warehouse. MATEC Web of Conferences. https://doi.org/10.1051/matecconf/201815401058

Körner, S., & Wahlgren, L. (2002). Praktisk statistik (3rd rev. ed.). Studentlitteratur. Lund.

Marziali, M., Rossit, D. A., & Toncovich, A. (2021). Warehouse Management and KPI Approach: A Case Study. Management and Production Engineering Review, 12(3), 51-62. DOI:10.24425/mper.2021.138530

McKinsey. (2011). Big data: The next frontier for innovation, competition, and productivity. McKinsey Global Institute. Retrieved from https://www.mckinsey.com/~/media/mckinsey/business%20functions/mckinsey%20digital/our%20insights/big%20data%20the%20next%20frontier%20for%20innovation/mgi_big_data_exec_summary.pdf

Nagorny, K., Barata, J., Monteiro, P. L., & Colombo, A. W. (2017). Big Data Analysis in Smart Manufacturing: A Review. International Journal of Communications, 10(03), 31-58. DOI:10.4236/ijcns.2017.103003

Parmenter, D. (2015). Key Performance Indicators (KPI): Developing, Implementing, and Using Winning KPIs (3rd ed.). Wiley. California.

Rushton, A., Croucher, P., & Baker, P. (2017). The handbook of logistics and distribution management. Kogan Page Publishers. London.

Shvets, V. Y., Shvets, L. W., & Dubey, J. V. (2014). How to create a KPI system to optimize warehousing complex operation? Challenges and Conceptions in Contemporary Logistics, 1, 11-120.

Staudt, F. H., Alpan, G., Di Mascolo, M., & Rodriguez, C. M. T. (2015). Warehouse performance measurement: A literature review. International Journal of Production Research, 53(18), 5524-5544.

Supply Chain Digital. (2021). Analytics & Automation: Changing the Face of Supply Chains. Supply Chain Digital. Retrieved April 23, 2023, from https://www.supplychaindigital.com/digital-supply-chain/analytics-automation-changing-the-face-of-supply-chains

TDAN. (2020, May 6). Data Management 20/20: Data Governance Challenges in a Digital Society. The Data Administration Newsletter. Retrieved April 23, 2023, from https://tdan.com/data-management-20-20-data-governance-challenges-in-a-digital-society/26599#

ThroughPut. (2021). AI in Supply Chain and Logistics. Retrieved April 23, 2023, from https://throughput.world/blog/ai-in-supply-chain-and-logistics/

Tokat, S., Karagul, K., Sahin, Y., & Aydemir, E. (2021). Fuzzy C-Means Clustering-Based Key Performance Indicator Design for Warehouse Loading Operations. Journal of King Saud University-Computer and Information Sciences.

Svensk Dos. (n.d.). Svensk Dos AB. Retrieved Dec 8, 2022, from https://www.svenskdos.se/

Wackerly, D. D., Mendenhall, W. M., & Scheaffer, R. L. (2008). Mathematical Statistics with Applications (7th ed.). Duxbury Advanced Series.

World Economic Forum. (2022, September 26). How manufacturing can use data and advanced analytics to unlock value. World Economic Forum. Retrieved April 23, 2023, from https://www.weforum.org/agenda/2022/09/manufacturing-data-advanced-analytics/

World Economic Forum. (2021). Data Excellence: Transforming manufacturing and supply systems. (White Paper January 2021). World Economic Forum. Cologny.

Publicering och arkivering

Godkända självständiga arbeten (examensarbeten) vid SLU publiceras elektroniskt. Som student äger du upphovsrätten till ditt arbete och behöver godkänna publiceringen. Om du kryssar i **JA**, så kommer fulltexten (pdf-filen) och metadata bli synliga och sökbara på internet. Om du kryssar i **NEJ**, kommer endast metadata och sammanfattning bli synliga och sökbara. Även om du inte publicerar fulltexten kommer den arkiveras digitalt. Om fler än en person har skrivit arbetet gäller krysset för samtliga författare. Du hittar en länk till SLU:s publiceringsavtal på den här sidan:

- https://libanswers.slu.se/sv/faq/228316.

☒ JA, jag/vi ger härmed min/vår tillåtelse till att föreliggande arbete publiceras enligt SLU:s avtal om överlåtelse av rätt att publicera verk.

☐ NEJ, jag/vi ger inte min/vår tillåtelse att publicera fulltexten av föreliggande arbete. Arbetet laddas dock upp för arkivering och metadata och sammanfattning blir synliga och sökbara.