

A methodological framework for mapping KPI interdependencies in the pharmaceutical industry: A matrix-based approach

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Abstract

The pharmaceutical industry, whose origins date back to the 15th century, has evolved into a complex research-intensive sector characterized by uncertainty in product development, the protection of intellectual property, and high profitability. In today's globalized and highly competitive environment, the ability to monitor and optimize organizational performance has become necessary. Key Performance Indicators have emerged as strategic tools for translating corporate objectives into measurable outcomes, guiding decision-making processes, and enhancing competitiveness. Therefore, this paper examines the strategic role of KPIs within pharmaceutical companies, highlighting their importance in aligning operations with corporate objectives and distinguishing between continuous manufacturing and discrete manufacturing. A methodological framework is proposed to analyze the interrelationships among KPIs, beginning with the selection of relevant indicators from the literature, the analysis of their mathematical formulations and underlying data, and progressing to the identification of interconnections between Base Data, Intermediate Metrics, and the KPIs. The application of this approach enables a deeper understanding of systemic effects in performance measurement by providing decision-makers with an analytical tool capable of mapping cause-and-effect relationships and predicting the impact of operational decisions on overall production performance.

Keywords

pharmaceutical industry, key performance indicators(KPIs), KPI interrelationships, performance measurement, strategic management, production capacity analysis

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1. Introduction

The evolution of the pharmaceutical industry has ancient origins, dating back to the 15th century, with the first Western pharmacopoeia, the 'Ricettario Fiorentino' in Florence in 1498, listing medicines and the rules for their preparation.¹ Later, structured lists of medicines appeared in Germany (1546) and the London Pharmacopoeia (1618) in England, where the foundation of the Society of Apothecaries (17th century) marked a milestone in the identification of the pharmacy as an autonomous entity, distinct from the apothecaries. The founding of the Pharmaceutical Society of Great Britain in 1841 opened a new chapter in the progress of official institutions related to pharmacy and the study of medicines.²

The 19th century is considered the period of the rise of the pharmaceutical industry as we understand it today, due to cultural-academic, scientific-technical and socioenvironmental factors. European universities, in particular medical schools,

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stimulated the acquisition of up-to-date knowledge in physics, biology and chemistry.³ Chemical research initially focused on the identification and preparation of commonly used drugs, before moving on to large-scale production and, in the second half of the century, the development of new synthetic substances related to dye chemistry.⁴

In recent decades, however, the global business environment has changed significantly, driven by globalization, technological transformation, and growing competitive pressures that have had a profound impact on corporate operations.⁵ To survive and thrive in such dynamic contexts, organizations have increasingly adopted new performance measurement and management systems,⁶ continuously adapting their performance metrics to rapidly evolving market conditions.⁷ A well-designed performance management system must integrate a comprehensive set of indicators, ensuring alignment with corporate strategies and stakeholder needs.^{8,9}

Within this framework, Key Performance Indicators (KPIs) have emerged as strategic tools for translating complex objectives into measurable outcomes. KPIs act as a compass guiding organizations toward their strategic goals, providing a structured basis for quantifying performance, identifying areas for improvement, and supporting informed decision-making.¹⁰⁻¹³ Their relevance is even more evident in industries with high Research and Development intensity, such as pharmaceuticals, which are characterized by uncertainty in product development, strong intellectual property protection requirements, and significant profitability.^{14,15} Therefore, the right selection and formulation of KPIs and the analysis of their interdependencies form the basis for improving production processes. However, an analysis of the current literature reveals that there are few scientific studies addressing KPIs in the pharmaceutical sector.

This lack of empirical research is likely attributable to the high levels of confidentiality in the pharmaceutical industry, which prevent the disclosure of performance data.¹⁶ Furthermore, the pharmaceutical environment is characterized by strict and constantly evolving quality regulations; these regulatory changes create a highly dynamic landscape in which KPIs must be recalibrated frequently to ensure compliance. This instability may have discouraged the development of specific studies in the past.¹⁶

In line with this need, this study starts in the context of IMPROVE Project (decision support system for Production management based on prediction of high impact Variables), funded by the Ministero delle Imprese e del Made in Italy (MIMIT), it addresses the industrial challenge of measuring and predicting production capacity in manufacturing environments. To achieve this goal, we need to analyze the specific dynamics of the pharmaceutical industry and the performance indicators that determine production capacity. A key element of this research is the collaboration with a partner pharmaceutical company, which served as the foundation and primary reference for our studies. Thanks to this partnership and the scientific literature, it was possible to define sector-specific KPIs and, to perform an analysis of the interdependencies existing between individual KPIs, as well as those linking KPIs to their underlying Base Data and Intermediate Metrics.

Consequently, this study develops a structured methodological framework designed to support managerial decision-making through three key objectives: firstly, to identify a specific set of KPIs relevant to the pharmaceutical sector; secondly, to characterise the discrete-continuous dynamics of the production process; and, thirdly, to map and quantify the interdependencies between the system's baseline data and performance indicators through the development of two operational matrices. These matrices provide a flexible framework that companies can adapt to their own specific operating conditions. By replicating this systematic approach, plant managers can derive tools tailored to their specific production layouts, ensuring that every strategic decision is thoroughly evaluated and that its operational implications are anticipated prior to practical implementation.

The study begins with Section 2 where there is an analysis of the literature on KPIs used in the manufacturing and pharmaceutical industry, and moves on to Section 3 dedicated to methodology, which explains the approach adopted to identify and analyse the interdependencies of KPIs. In Section 4 the work provides an analysis of the dynamics of pharmaceutical systems, describing the reference system used to calibrate the analytical model. The specific KPIs for the system under examination are detailed in Section 5, integrating the indicators identified in the literature with the specific operational requirements of the case study. Finally, in Section 6 the results are presented and discussed, concluding with an analysis of the study's limitations and proposed directions for future research in Section 7.

2. Literature review - the importance of KPIs and relationships between KPIs

In the dynamic field of process optimisation, Key Performance Indicators play a central role in assessing and guiding organisational performance.¹⁷ KPIs are metrics designed to quantify the effectiveness and efficiency of performance against strategic objectives.^{18,19} They act as analytical variables, steering operations towards higher standards through continuous monitoring that provides an understanding of the current position relative to set targets.²⁰⁻²² KPIs support evidence-based decision-making and are capable of managing the complexity of modern markets, characterised by increasingly short product life cycles, by adapting to them. The integration of KPIs into real-time control systems and interactive dashboards enables granular operational oversight, facilitating trend analysis and the identification of root causes.^{22,23} This approach enables the implementation of corrective and preventive actions, triggering a virtuous cycle of continuous improvement and promoting

sustainability through asset optimisation and waste reduction.²⁴ From a strategic perspective, KPIs ensure alignment between the corporate vision and day-to-day activities, often facilitated by established frameworks such as the Balanced Scorecard.¹⁷

Another important aspect of performance evaluation is the analysis of quantitative interdependencies between indicators. The literature highlights how cause-and-effect relationships between KPIs can generate cascading effects: for example, an increase in Preventive Maintenance Time can lead to a reduction in wear-and-tear failures, positively influencing the number of Failure Events and reducing the system's technical downtime.¹⁷ Ignoring the cascading effects of these interrelationships can lead to misleading overestimates of the benefits derived from improvement actions, compromising the accuracy of overall efficiency calculations.

To model these industrial interdependencies, academic literature has adopted Multicriteria Decision-Making methodologies, each characterized by specific operational structures:

Interpretative Structural Modeling (ISM) is used to establish a hierarchical structure among system metrics; However, it operates on a binary relational scale (representing only the presence or absence of a connection, 0 or 1), which prevents it from quantifying the actual numerical intensity of KPI propagation.²⁵

The Decision-Making Trial and Evaluation Laboratory (DEMATEL) is used to classify a system's KPIs into "cause" or "effect" clusters, but its mathematical output depends on subjective and qualitative scaling assignments (such as expert panel scales from 0 to 4) rather than actual, physical production data.²⁶

The Analytical Network Process (ANP) maps feedback networks resulting from pairwise comparisons of KPIs by experts to determine their relative importance. However, this method produces static priority weights (relative importance) rather than physical and mathematical formulas. Furthermore, comparing dozens of operating variables in pairs requires a large amount of subjective questionnaires, making it too rigid.²⁷

Consequently, there is a methodological gap: existing models fail to translate localized quantitative variations in physical production data into direct mathematical calculations of overall system performance. To bridge this gap, this article introduces a new matrix-based framework. By linking physical process data to key performance indicators (KPIs) through a system of sensitivity matrices and linkages between the various levels of KPIs, the proposed approach relies on an objective, data-driven simulation of operational interdependencies, rather than on subjective, opinion-based assessments.

This paper aims to move beyond partial views of performance measurement, seeking a holistic and integrated understanding of the production system. Through the development of two sensitivity matrices, this paper provides an advanced analytical tool capable of reflecting not only the direct dependence between Key Performance Indicators and Basic Data, but also the complex interrelationships between the KPIs themselves and Intermediate Metrics. This approach enables the mapping of uncertainty propagation across the entire hierarchical structure of the model, transforming measurement into a decision-support architecture. Analysing these multidimensional links enables management to pinpoint the key operational levers, anticipate the knock-on effects of corrective actions and balance the trade-offs between different performance domains, thereby maximising the strategic effectiveness of improvement initiatives.

2.1. KPIs in pharmaceutical industry

Key Performance Indicators in the pharmaceutical sector stem from the need to ensure the quality, safety and efficacy of medicines in a highly regulated global market.²⁸ These indicators arise from the integration of Quality Assurance (QA) requirements and Operational Excellence (OPEX) programmes, with the aim of monitoring processes and identifying potential risks.^{29,30} The various regulations governing this sector form a complex and interconnected ecosystem, as follows:

Good Manufacturing Practices (GMP): These are the minimum requirements that manufacturers must meet to ensure that products are of consistently high quality and safe for their intended use.³¹ GMP covers every aspect of production, from the control of raw materials to staff training.

ICH Q10: This international guideline describes a Pharmaceutical Quality System (PQS) model based on ISO quality concepts.²⁸ It complements (GMP) and aims to promote a cycle of continuous improvement throughout the product lifecycle.

Good Laboratory Practices (GLP) and Good Clinical Practices (GCP): GLP regulates non-clinical laboratory research to ensure the integrity of safety data, whilst GCP sets out the ethical and scientific standards for the conduct of clinical trials on humans.³¹

ISO 22400 standard (Key Performance Indicators for Manufacturing Operations Management): provides the structural framework for the technical development of operational metrics. Adoption of this standard enables the harmonisation of pharmaceutical KPIs within a standardised manufacturing language.

These standards and their associated KPIs work together synergistically to create a robust Quality Infrastructure.²⁴

In industrial systems, quality, time and performance, and maintenance are three intrinsically interconnected areas that cannot be assessed in isolation: indeed, whilst Maintenance directly affects equipment availability and time efficiency (Time), it also influences process stability and, consequently, the rate of defective products (Quality). Conversely, poor equipment condition resulting from inadequate maintenance leads to operational breakdowns, downtime and reduced quality.

To model and measure these multidirectional dependencies, the literature suggests integrating maintenance, quality and production efficiency into a single indicator: Overall Equipment Effectiveness (OEE).³² OEE serves as a mathematical synthesis of this triad, as its formulation intrinsically balances availability (Time), performance and the quality rate (Quality), all of which are influenced by the physical condition of the equipment (Maintenance).³³ Consequently, Table 1 lists the most recognized KPIs identified in the scientific literature, categorized into these three core domains, which directly converge to provide the structured inputs necessary for calculating the OEE.

It should be noted that, despite the central importance of performance measurement, the scientific literature lacks structured and standardised KPIs frameworks specific to the pharmaceutical industry. This gap can be attributed to the complexity of production processes and the time constraints imposed by strict regulatory requirements, which often slow down the adoption of innovative methodologies. Indeed, there is widespread resistance to integrating Lean Management practices and dynamic monitoring systems, stemming from the fear that such changes may compromise regulatory compliance.¹⁶ However, it is important to note that international guidelines, in particular ICH Q10, explicitly promote continuous improvement and constant performance monitoring as pillars for ensuring superior quality standards.

A further critical issue in the pharmaceutical sector is a reluctance to disclose its quality indicators and related results.¹⁶ This lack of public information and shared reference models hinders the development of universal frameworks, limiting the possibility of effective benchmarking. Consequently, research is conducted within a context characterised by fragmented information, making it necessary to develop models, such as the one proposed in this paper, that reconcile the need for operational efficiency with the sector's confidentiality and compliance requirements.

3. Methodology for analyzing interdependencies between KPIs

The study on the interdependencies between Key Performance Indicators in the pharmaceutical industry was conducted using a methodological approach structured in three sequential phases:

3.1. Study of the pharmaceutical system's dynamics

Initially, a study was carried out on the layout and processes of the pharmaceutical system under investigation. This phase combined an analysis of the scientific literature in the sector with information provided by the partner company, enabling the operational specifications of the production lines to be outlined.

Table 1. Main KPIs for manufacturing and pharmaceutical industry.

C	KPI	Formulation	References
Q	Deviation Ratio (DR) [%]	$\frac{\text{Number of Deviations}}{\text{Number of Check Activities}} \times 100$	16,24
	Scrap Ratio (SR) [%]	$\frac{\text{Scrapped Quantity}}{\text{Produced Quantity}} \times 100$	18,34–36
	Right First Time (RFT) [%]	$\frac{\text{Quantity completed without rework}}{\text{Produced Quantity in the first process}} \times 100$	16,24,34,37
	Rework Ratio (RWR) [%]	$\frac{\text{Reworked Quantity}}{\text{Produced Quantity}} \times 100$	14,16,34,35,37
	Quality Ratio (QR) [%]	$\frac{\text{Total Production} - \text{Defect Amount}}{\text{Total Production}} \times 100$	37–40
	First Pass Yield (FPY) [%]	$\frac{\text{Quantity Compliant at First Test}}{\text{Total Units Tested}} \times 100$	34–37
	First Time Quality (FTQ) [%]	$\frac{\text{Good Quantity}}{\text{Produced Quantity in First Process}} \times 100$	16,24,34,36,37
T	Performance Efficiency (P) [%]	$\frac{\text{Cycle Time (Processing Time)} \times \text{Actual Output}}{\text{Operating Time}} \times 100$	37,40
	Availability Rate (A) [%]	$\frac{\text{Operating Time}}{\text{Loading Time}} \times 100$	37,40
	Planned Throughput (PT) [kg/h]	$\frac{\text{Planned Processing Quantity}}{\text{Planned Busy Time}}$	37
	Actual Throughput (AT) [kg/h]	$\frac{\text{Actual Processing Quantity}}{\text{Planned Busy Time}}$	37
M	Mean Time Between Failure (MTBF) [h]	$\frac{\text{Total Operating Time}}{\text{Failure Events}}$	41
	Mean Time To Repair (MTTR) [h]	$\frac{\text{Total Repair Time}}{\text{Repair Events}}$	41
	Corrective Maintenance Ratio (CMR) [%]	$\frac{\text{Corrective Maintenance Time}}{\text{Corrective+Preventive Maint. Time}} \times 100$	18,35

3.2. Multi-level modelling and calculation

Subsequently, the computational architecture was defined and implemented using advanced calculation tools (Excel). The model involved the application of KPIs derived from the literature across three levels of increasing aggregation:

Continuous System Level: analysis of the performance of constant-flow stages (gel formation and, subsequently, granule formation);

Discrete System Level: analysis of the performance of defined-cycle phases (encapsulation, blistering and packaging);

Entire System: integration and manipulation of metrics from individual systems to obtain a holistic view of the system's performance.

It should be noted that, in order to ensure the confidentiality of sensitive information and the privacy of the system under study, the numerical data reported in the model are illustrative and indicative.

3.3. Sensitivity analysis

By varying the BD, i.e. the input parameters, it was possible to observe the resulting variation in the KPIs at different levels. This process enabled the quantification of how operational variations impact the KPIs.

The application of this methodology led to the generation of two analytical tools useful for understanding the system and analysing interdependencies:

Sensitivity Impact Matrix (SIM): a tool that identifies which input variables directly or indirectly influence the various KPIs and in what way.

Intermediate Linkage Matrix (ILM): a detailed map that breaks down the KPI BD link by introducing an additional level of Intermediate Metrics, which is useful for understanding indirect interrelationships as well. This is a completely innovative tool compared to the scientific literature.

4. Case study - pharmaceutical system

This study focuses on pharmaceutical systems specialising in the manufacture of medicinal capsules. This type of system is unique because it is a hybrid production line, consisting of a first continuous process, which handles gel production, and a second discrete process, which handles the production of capsules, which are then inserted into product blister packs.^{42,43} This distinction is fundamental because it is not limited to the nature of the products, but also involves the type of system, the management of process variables, work organisation and production flexibility. Consequently, this distinction also has a decisive impact on the definition and monitoring of Key Performance Indicators. The fundamental difference between the two phases can be summarised as follows⁴⁴:

Continuous Production: is characterised by a constant, uninterrupted flow of materials through the system. In this phase, output is measured in terms of throughput or volume.

Discrete Production: this involves the manufacture of distinct and identifiable physical units. In this case, the production flow can be interrupted, restarted or modified according to requirements or orders.

For the analysis of interdependencies, the actual layout of the partner company's system was translated into a simplified model designed to capture its fundamental dynamics. The study does not go into detail regarding individual workstations; instead, groups of continuous-cycle and batch-cycle machines were modelled, respectively, as a continuous system and a discrete system.

In this architecture, both macro-systems were treated as a single equipment (understood as a black box containing the various machines). This approach allows the KPIs derived from the literature, previously summarised in [Table 1](#), which were originally designed for individual equipment, to be applied to each system. Subsequently, these KPIs applied to the individual systems were manipulated and aggregated according to established methodologies in the literature to calculate the KPIs for the entire system. The focus of the research thus shifts from the analysis of elementary components to the study of interdependencies between global indicators, ensuring a holistic view of the operational performance of the entire system.

[Figure 1](#) shows the pharmaceutical system which, as explained previously, is modelled through the functional grouping of machines into two distinct blocks:

The continuous production system: analysed as a single integrated stage aimed at the preparation of semi-finished material (granular powder).

The discrete production system: understood as a unified grouping of machines responsible for the production of identifiable physical units (capsules).

The conversion between the Continuous system and the Discrete system is possible thanks to the known physical conversion factor, namely the mass of powder per capsule. To illustrate this conversion from mass to units over a shared time horizon (for example on an hourly basis), the relationship is defined as:

$$1 \text{ capsule} = x \text{ mg of powder}$$

Consequently, this parameter acts as a scaling factor to convert the continuous mass of material (kg) into a discrete number of capsules, thereby aligning the hourly productivity of both production phases.

This approach allows each of the two stages to be treated in its entirety and uniqueness, focusing attention on the performance KPIs of the individual systems and the entire system.

4.1. Elements of the pharmaceutical system

In order to assess the system's efficiency, it is necessary to define the constituent elements of the system's information infrastructure, from which the KPIs are derived.³⁵ These elements represent the monitored variables that directly reflect operational performance and can be classified into two main categories:

Base Data: consists of the input variables of production processes. These represent the variables that can be adjusted to achieve improved performance.

Intermediate Metrics: are indicators derived from the combination of BD. The metrics provide a relative and contextualised assessment of performance. They act as a link between the BD and the KPIs.

To provide a comprehensive overview of the system's performance, the elements identified as Base Data and Intermediate Metrics are categorized into three primary domains: Quality, Time and Maintenance. These domains represent the pillars from which the final KPIs are calculated.

4.1.1. Quantity elements

The quantity elements provide information on issues related to product quality and quantity. Starting with the element provided in International Standard ISO 22400-2 (2014) and those defined in the studies by Kang³⁵ and Bhadani,³⁷ the quantity elements for the pharmaceutical system are shown in Figure 2 and it has been defined as follows:

4.1.1.1. Continuous system

Raw Materials (RM): The raw materials entering the entire process.

Produced Quantity (PQ): The total quantity produced by the entire system (including scrapped items).

Conforming Quantity - continuous system (CQ_c): The conforming quantity produced at the end of continuous production.

Scrap Quantity - continuous system (SQ_c): The produced quantity that does not meet quality requirement of the continuous process and has to be scrapped.

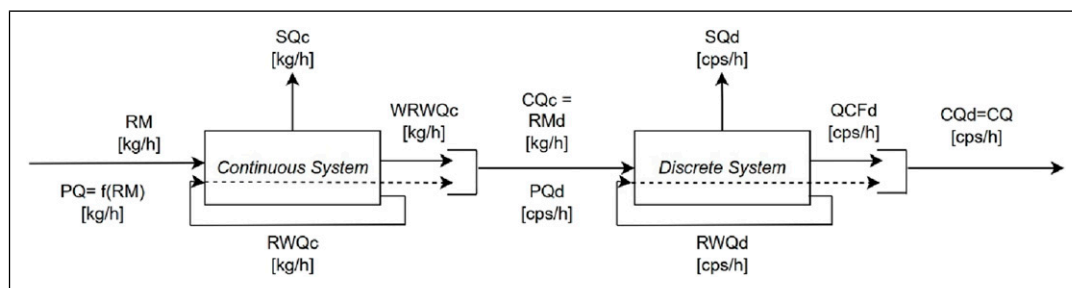


Figure 1. Pharmaceutical system.

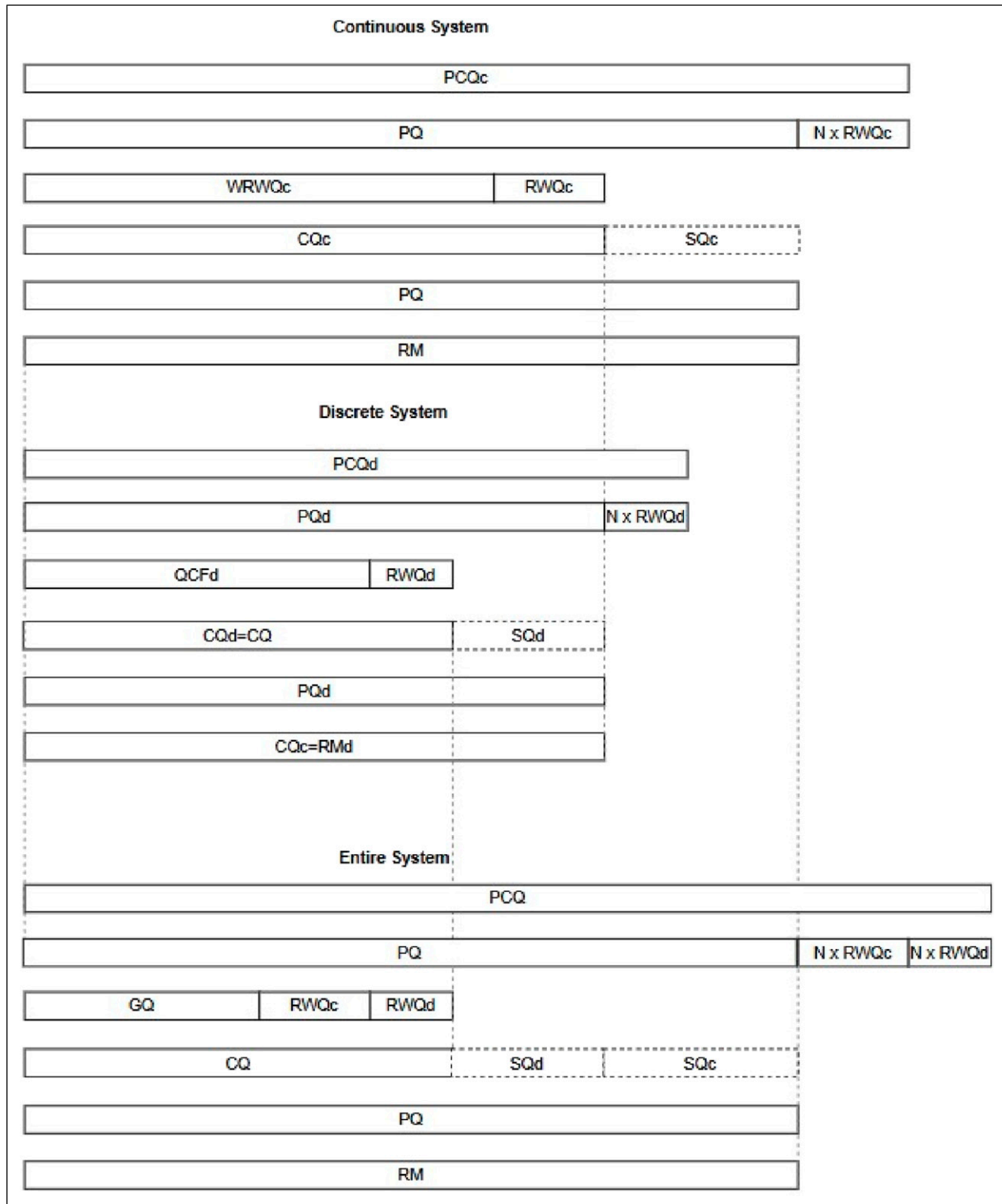


Figure 2. Quantity elements.

Without Rework Quantity - continuous system (WRWQ_c): The produced quantity that meets quality requirement in the first time of the continuous process.

Rework Quantity - continuous system (RWQ_c): The quantity that fails to meet the quality requirements, but reaches the required quality standards through additional continuous processing. Post-rework, these units are considered fully compliant.

Processed Quantity - continuous system (PCQ_c): The total quantity processed by the continuous system to produce the PQ (including all quantity that is reworked by the continuous system).

The relationship between the continuous system's quantities can be described as follows:

$$PQ = f(RM) \quad (1)$$

$$PQ = CQ_c + SQ_c \quad (2)$$

$$CQ_c = WRWQ_c + RWQ_c \quad (3)$$

$$PCQ_c = PQ + N \times RWQ_c \quad (4)$$

Where N is the number of continuous reworked activities. **Discrete system.**

Raw Materials - discrete system (RM_d): The raw materials entering the discrete process.

Produced Quantity - discrete system (PQ_d): The total quantity produced by the discrete system (including scrapped items).

Conforming Quantity - discrete system (CQ_d): The conforming quantity produced at the end of discrete production.

Scrap Quantity - discrete system (SQ_d): The produced quantity that does not meet quality requirement of the discrete process and has to be scrapped.

Quantity Compliant at First Time - discrete system (QCF_d): The quantity produced that meets the quality requirement in the first time of the discrete process.

Rework Quantity - discrete system (RWQ_d): The quantity that fails to meet the quality requirements, but reaches the required quality standards through additional discrete processing. Post-rework, these units are considered fully compliant.

Processed Quantity - discrete system (PCQ_d): The total quantity processed by the discrete system to produce the PQ_d (including all quantity that is reworked by the discrete system)

The relationship between the discrete system's quantities can be described as follows:

$$PQ_d = f(RM_d) = f(CQ_c) \quad (5)$$

$$PQ_d = CQ_d + SQ_d \quad (6)$$

$$CQ_d = CQ = QCF_d + RWQ_d \quad (7)$$

$$PCQ_d = PQ_d + N \times RWQ_d \quad (8)$$

Where N is the number of discrete reworked activities.

4.1.1.2. Entire system

Conforming Quantity (CQ): The conforming quantity produced at the end of production.

Good Quantity (GQ): The quantity produced that meets the quality requirement in the first time of the entire process.

Processed Quantity (PCQ): The total quantity processed by the entire system to produce the PQ (including all material that is reworked)

The relationship between the entire system's quantities can be described as follows:

$$PQ = f(RM) \quad (9)$$

$$CQ = PQ - SQ_c - SQ_d \quad (10)$$

$$GQ = CQ - RWQ_c - RWQ_d \quad (11)$$

$$PCQ = PQ + N \times RWQ_c + N \times RWQ_d \quad (12)$$

4.1.2. Time elements

Time elements represent data points defining the duration of operations within production systems. These metrics characterize both manufacturing and maintenance activities. In a production environment, such intervals can be analyzed from the perspective of the equipment, the production order, or the operator. Starting with the elements provided in the International Standard ISO 22400-2 (2014) and those defined in the studies by Nachiappan⁴⁵ and Bhadani,³⁷ these studies define time elements relating to the pharmaceutical system from the perspective of equipment, as shown in Figures 3 and 4.

4.1.2.1. Continuous (discrete) system

Valuable Operating Time - continuous (discrete) system ($VOT_{c(d)}$): Time in which the continuous (discrete) system is producing for a conforming quantity, which only includes the value-adding functions.

Non-Valuable Operating Time - continuous (discrete) system ($NVOT_{c(d)}$): Time in which the continuous (discrete) system is producing for a non-conforming quantity, which only includes the non-value-adding functions.

Net Operating Time - continuous (discrete) system ($NOT_{c(d)}$): Time in which the continuous (discrete) system is producing the total quantity.

Actual Equipment No Processing Time - continuous (discrete) system ($AENPT_{c(d)}$): Actual time when the continuous (discrete) system is not executing a processing operation to the desired specification, although it is available.

In the pharmaceutical industry:

$$AENPT_c = STUT_c \quad (13)$$

$$AENPT_d = STUT_d \quad (14)$$

where $STUT_c$ is the Startup Time of the continuous system, and $STUT_d$ is the Startup Time of the discrete system.

Operating Time - continuous (discrete) system ($OT_{c(d)}$): Time in which the continuous (discrete) system is available to be used for a process operation.

Actual Equipment Down Time - continuous (discrete) system ($AEDT_{c(d)}$): Actual time in which the continuous (discrete) system is not available due to unscheduled maintenance, failure etc.

In the pharmaceutical industry:

$$AEDT_c = CMT_c \quad (15)$$

$$AEDT_d = CMT_d + SUT_d \quad (16)$$

where CMT_c is the Corrective Maintenance Time of the continuous system; CMT_d is the Corrective Maintenance Time, and SUT_d is the Setup Time of the discrete system.

Planned Busy Time - continuous (discrete) system ($PBT_{c(d)}$): Time in which the continuous (discrete) system is planned to perform material processing.

Planned Down Time - continuous (discrete) system ($PDT_{c(d)}$): Time for planned maintenance work to be performed on the continuous (discrete) system.

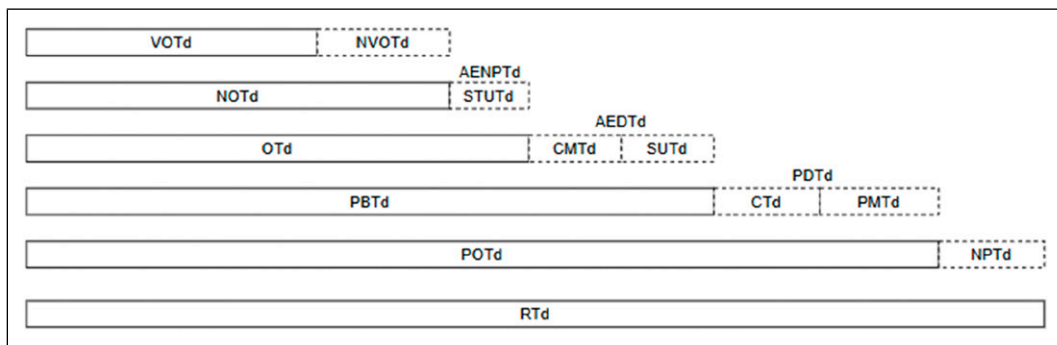


Figure 3. Time elements of continuous system.

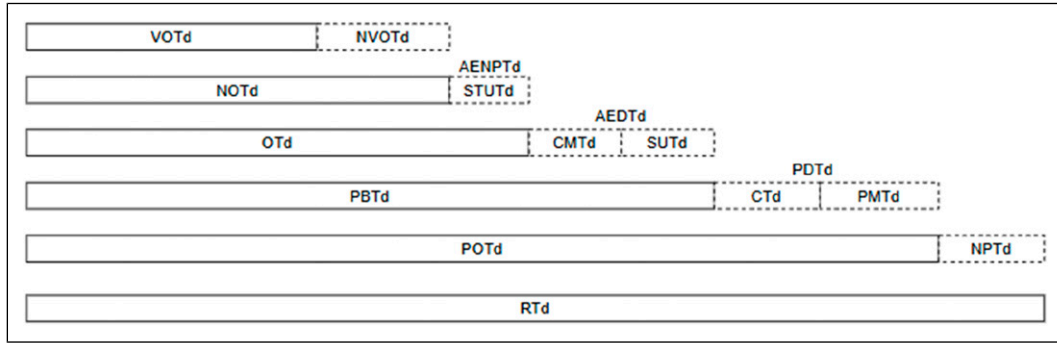


Figure 4. Time elements of discrete system.

In the pharmaceutical industry:

$$PDT_c = CT_c + PMT_c \quad (17)$$

$$PDT_d = CT_d + PMT_d \quad (18)$$

where CT_c is Cleaning Time, and PMT_c is Preventive Maintenance Time of the continuous system; CT_d is Cleaning Time, and PMT_d is Preventive Maintenance Time of the discrete system.

Planned Operation Time - continuous (discrete) system ($POT_{c(d)}$): Time wherein the continuous (discrete) system is planned to be operated.

No Processing Time - continuous (discrete) system ($NPT_{c(d)}$): Time during which the scheduling of the process operation wherein the continuous (discrete) process is shut down.

Reference Time - continuous (discrete) system ($RT_{c(d)}$): Time for which the operations are being observed for the KPI calculations in the continuous (discrete) system.

The relationship between these quantities can be described as follows, distinguishing between the two individual systems:

$$NOT_{c(d)} = VOT_{c(d)} + NVOT_{c(d)} \quad (19)$$

$$OT_{c(d)} = NOT_{c(d)} + STUT_{c(d)} \quad (20)$$

$$PBT_{c(d)} = OT_{c(d)} + CMT_{c(d)} (+SUT_d) \quad (21)$$

$$POT_{c(d)} = PBT_{c(d)} + CT_{c(d)} + PMT_{c(d)} \quad (22)$$

$$RT_{c(d)} = POT_{c(d)} + NPT_{c(d)} \quad (23)$$

4.1.3. Maintenance elements

Maintenance elements serve to document activities related to equipment maintenance and repair. Building upon the framework established by the ISO 22400–2 (2014) International Standard, the studies of Kang,³⁵ Ali⁴¹ and Shabaninejad¹⁸ this section defines or modifies key maintenance elements as follows:

Time Between Failure - continuous (discrete) system ($TBF_{c(d)}$): The actual unit production time between two consecutive failures of a system.

Time To Repair - continuous (discrete) system ($TTR_{c(d)}$): The actual time during which a continuous (discrete) system is unavailable due to a failure, i.e. under repair. Note that it is assumed that the Time To Repair is equal to the Corrective Maintenance Time:

$$TTR_c = CMT_c \quad (24)$$

$$TTR_d = CMT_d \quad (25)$$

Failure Event - continuous (discrete) system ($FE_{c(d)}$): The total number of events within a specific time interval in which the continuous (discrete) system loses its ability to perform a required function.

Repair Event - continuous (discrete) system ($RE_{c(d)}$): The total number of occurrences within a given time period in which the continuous (discrete) system resumes its ability to perform a required function. It is assumed that the number of Repair Events is equal to the number of Failure Events.

Failure Rate - continuous (discrete) system ($\lambda_{c(d)}$): It is a metric that measures the frequency with which the continuous (discrete) system fails over a given period of time.

Corrective Maintenance Time - continuous (discrete) system ($CMT_{c(d)}$): The duration within the total maintenance period dedicated to performing corrective actions to restore the continuous (discrete) system to its operational state.

Preventive Maintenance Time - continuous (discrete) system ($PMT_{c(d)}$): The duration within the total maintenance period allocated for scheduled activities aimed at preventing continuous (discrete) system failure.

5. Calculating KPIs: From literature to practice

Following a detailed characterization of the pharmaceutical system and its operational features, the KPIs previously identified in the literature and international standards are applied and calculated for this specific case study. The case study was employed to align and verticalize the KPIs found in the literature within a real-world industrial context. However, it should be noted that the data populated in the model are indicative, because of confidentiality agreements; therefore, the values do not represent the actual operational figures of the company involved.

Table 2 summarizes the formulations for each KPI across the three proposed perspectives: continuous, discrete, and entire systems. Specifically, for both continuous and discrete systems, the specific formulations are derived by integrating the general equations presented in Table 1 with the distinct system characterizations detailed in Section 4. Conversely, for the entire system, the Quality KPIs follow this same approach, combining the general framework of Table 1 with the system characterizations from Section 4. However, the Time and Maintenance KPIs are drawn from established scientific literature regarding compound system KPIs, as specified in Table 2.

6. Sensitivity analysis and results

Sensitivity analysis (SA) is defined as the study of how uncertainty in the output of a mathematical model, whether a single key performance indicator or a complex composite index, can be attributed to the various sources of uncertainty present in the underlying input factors.⁴⁹ Within the context of this pharmaceutical case study, SA represents a step towards ensuring the validation and corroboration of the proposed metrics. By simulating variations in the underlying data, the analysis checks whether the KPIs remain robust or are sensitive to such variations. This process enhances the transparency and defensibility of the performance measurement system, providing objective evidence of which variables actually determine the results.⁵⁰

From a strategic management perspective, the application of SA offers distinct operational areas that go beyond simple data verification. First, through “factor prioritization,” the analysis identifies the few critical input variables that account for most of the variation in output; identifying these key factors allows management to focus interventions and investments on specific areas that ensure the greatest impact on overall efficiency.⁵¹ Furthermore, factor mapping allows for the identification of specific combinations of inputs that risk pushing the system into critical areas.⁵² This comprehensive approach transforms the KPI from a static descriptive tool into a dynamic and actionable roadmap for continuous improvement. In this way, decision-makers have useful tools for reactive monitoring, in which every technical intervention is precisely targeted at the most sensitive levers of the production process.

The primary result of the sensitivity analysis is the **Sensitivity Impact Matrix (SIM)**, a structured framework that maps the functional relationships between Base Data (input variables) and Key Performance Indicators. To evaluate the operational dependencies within the system, the SIM was constructed by applying a variation to each Base Data; specifically, the magnitude of this variation was set to a full nominal length (−100% around the reference value). This wide-range scenario analysis acts as a comprehensive stress test, evaluating system behavior across its entire theoretical operational envelopes. The impact magnitude is quantified via the sensitivity coefficient S_{ij} :

$$S_{ij} = \frac{\Delta \% KPI_i}{\Delta \% BD_j} \quad (26)$$

Table 2. Performance indicators for pharmaceutical production: Quality, time, and maintenance.

Category	System type	Specific KPI	Formulation	References
Quality	Continuous	DR [%]	$\frac{\text{Number of Deviations (ND)}}{\text{Number of Check Activities (NCA)}} \times 100$	
		SRc [%]	$\frac{SQc}{PQ} \times 100$	
		RFTc [%]	$\frac{WRWQc}{PQ} \times 100$	
		RWRc [%]	$\frac{RWQc}{PQ} \times 100$	
	Discrete	QRc [%]	$\frac{CQc}{CQc+SQc} \times 100$	
		SRd [%]	$\frac{SQd}{PQd} \times 100$	
		FPYd [%]	$\frac{QCF}{PQd} \times 100$	
		RWRd [%]	$\frac{RWQd}{PQd} \times 100$	
	Entire	QRd [%]	$\frac{CQd}{CQd+SQd} \times 100$	
		SR [%]	$\frac{SQc+SQd}{PQ} \times 100$	
		FTQ [%]	$\frac{GQ}{PQ} \times 100$	
		RWR [%]	$\frac{RWQc+RWQd}{PQ} \times 100$	
	Continuous	QR [%]	$QRc + QRd$	
		Pc [%]	$\frac{NOTc}{OTc} \times 100$	
Time	Continuous	Ac [%]	$\frac{OTc}{PBTc} \times 100$	
		PTc [kg/h]	$\frac{PQ}{PBTc}$	
		ATc [kg/h]	$\frac{CQc}{PBTc}$	
		TRc [%]	$\frac{ATc}{PTc} \times 100$	
	Discrete	Pd [%]	$\frac{NOTd}{OTd} \times 100$	
		Ad [%]	$\frac{OTd}{PBTd} \times 100$	
		PTd [cps/h]	$\frac{PQd}{PBTd}$	
		ATd [cps/h]	$\frac{CQd}{PBTd}$	
	Entire	TRd [%]	$\frac{ATd}{PTd} \times 100$	
		P [%]	$\min \{Pc; Pd\}$	38
		A [%]	$Ac \times Ad$	46
		TR [%]	$\min \{TRc; TRd\}$	47
Maintenance	Continuous	MTBFC [h]	$\frac{PBTc}{FEC}$	
		MTTRc [h]	$\frac{\text{Total repair time}_c}{REC}$	
	Discrete	CMRc [%]	$\frac{CMTc}{PMTc+CMTc} \times 100$	
		MTBFD [h]	$\frac{PBTd}{FED}$	
	Entire	MTTRd [h]	$\frac{\text{Total repair time}_d}{RED}$	
		CMRd [%]	$\frac{CMTd}{PMTd+CMTd} \times 100$	41
	Entire	MTBF [h]	$\frac{1}{\lambda}$	41,48
		MTTR [h]	$\left(\frac{MTBF}{A}\right) - MTBF$	18,35
	Continuous	CMR [%]	$\frac{CMTc+CMTd}{\sum (PMT+CMT)_{c,d}} \times 100$	

Where $\Delta \% BD_j$ represents the specific variation applied to the j^{th} base data and $\Delta \% KPI_i$ is the resulting change observed in the i^{th} performance indicator. Due to the linear structure of the underlying model equations, this ratio remains constant, ensuring that S_{ij} accurately reflects the global sensitivity and scaling factor of each parameter.

This matrix (Tables 3–5) serves as a multi-directional diagnostic tool, offering significant advantages for the strategic management of pharmaceutical manufacturing performance.

Adopting a **top-down perspective**, the matrix serves as a decision-support tool for performance enhancement. This approach allows management to deconstruct operational dynamics through three analytical dimensions:

Variable Identification: By isolating the column associated with a specific target KPI, management can discern the subset of input variables that exert influence on that indicator. This granularity ensures that the focus remains on relevant drivers.

Table 3. Sensitivity impact matrix (SIM) - section 1: Quality.

Quality													
Variables	Continuous system				Discrete system				Entire system				
	DRC	SRc	RFTc	RWRc	QRc	SRd	FPYd	RWRd	QRd	SR	FTQ	RWR	QR
NCA	1,0000	1,0000	-0,0213	*	-0,0204	*	*	*	*	0,3927	-0,0214	-0,0135	-0,0204
ND	1,0000	1,0000	-0,0213	*	-0,0204	*	*	*	*	0,3927	-0,0214	-0,0135	-0,0204
RWQc	*	*	-0,0426	1,0000	*	*	*	*	*	*	-0,0481	0,3378	*
FEC	*	*	*	*	*	*	*	*	*	*	*	*	*
STUTc	*	*	*	*	*	*	*	*	*	*	*	*	*
CMTc	*	*	*	*	*	*	*	*	*	*	*	*	*
CTc	*	*	*	*	*	*	*	*	*	*	*	*	*
PMTc	*	*	*	*	*	*	*	*	*	*	*	*	*
SQd	*	*	*	*	*	1,0000	-0,0337	*	-0,0309	0,5951	-0,0353	*	-0,0309
RWQd	*	*	*	*	*	*	-0,0899	1,0000	*	*	-0,0942	0,6622	*
FEd	*	*	*	*	*	*	*	*	*	*	*	*	*
STUTd	*	*	*	*	*	*	*	*	*	*	*	*	*
CMTd	*	*	*	*	*	*	*	*	*	*	*	*	*
SUTd	*	*	*	*	*	*	*	*	*	*	*	*	*
CTd	*	*	*	*	*	*	*	*	*	*	*	*	*
PMTd	*	*	*	*	*	*	*	*	*	*	*	*	*

Note. The presence of a positive correlation implies a direct relationship between the input and the output: a positive sign (+) indicates a direct correlation (the KPI increases as the *BD* increases), while a negative sign (−) signals an inverse relationship (the KPI decreases as the *BD* increases, vice versa).

Table 4. Sensitivity impact matrix (SIM) - section 2: Time.

Time													
Variables	Continuous system				Discrete system				Entire system				
	Pc	Ac	PTc	ATc	TRc	Pd	Ad	PTd	ATd	TRd	P	A	TR
NCA	*	*	*	-0,0204	-0,0204	-0,0001	-0,0011	-0,0012	-0,0012	*	*	-0,0011	*
ND	*	*	*	-0,0204	-0,0204	-0,0001	-0,0011	-0,0012	-0,0012	*	*	-0,0011	*
RWQc	0,0015	0,0011	-0,0373	-0,0373	*	*	*	*	*	*	0,0015	0,0011	*
FEC	*	*	*	*	*	*	*	*	*	*	*	*	*
STUTc	-0,0385	0,0011	-0,0373	-0,0373	*	*	*	*	*	*	-0,0340	0,0011	*
CMTc	*	-0,0289	-0,0289	-0,0289	*	*	*	*	*	*	*	-0,0289	*
CTc	*	*	*	*	*	*	*	*	*	*	*	*	*
PMTc	*	*	*	*	*	*	*	*	*	*	*	*	*
SQd	*	*	*	*	*	*	*	*	-0,0309	-0,0309	*	*	-0,0103
RWQd	*	*	*	*	*	0,0003	0,0044	-0,0749	-0,0749	*	*	0,0044	*
FEd	*	*	*	*	*	*	*	*	*	*	*	*	*
STUTd	*	*	*	*	*	-0,0043	0,0002	-0,0041	-0,0041	*	*	0,0002	*
CMTd	*	*	*	*	*	*	-0,0494	-0,0494	-0,0494	*	*	-0,0494	*
SUTd	*	*	*	*	*	*	-0,0082	-0,0082	-0,0082	*	*	-0,0081	*
CTd	*	*	*	*	*	*	*	*	*	*	*	*	*
PMTd	*	*	*	*	*	*	*	*	*	*	*	*	*

Note. The presence of a positive correlation implies a direct relationship between the input and the output: a positive sign (+) indicates a direct correlation (the KPI increases as the BD increases), while a negative sign (-) signals an inverse relationship (the KPI decreases as the BD increases, vice versa).

Table 5. Sensitivity impact matrix (SIM) - section 3: Maintenance.

Maintenance									
Variables	Continuous system			Discrete system			Entire system		
	MTBFc	MTTRc	CMRc	MTBFd	MTTRd	CMRd	MTBF	MTTR	CMR
NCA	*	*	*	-0,0192	*	*	-0,0090	0,0046	*
ND	*	*	*	-0,0192	*	*	-0,0090	0,0046	*
RWQc	0,0360	*	*	*	*	*	0,0193	0,0063	*
FEC	1,0000	1,0000	*	*	*	*	-1,1101	-1,1101	*
STUTc	0,0360	*	*	*	*	*	0,0193	0,0063	*
CMTc	0,0281	1,0000	1,0000	*	*	*	0,0150	0,3536	0,1341
CTc	*	*	*	*	*	*	*	*	*
PMTc	*	*	-3,2051	*	*	*	*	*	-0,4044
SQd	*	*	*	*	*	*	*	*	*
RWQd	*	*	*	0,0697	*	*	0,0343	-0,0176	*
FEd	*	*	*	1,0000	1,0000	*	-0,9008	-0,9008	*
STUTd	*	*	*	0,0041	*	*	0,0019	-0,0010	*
CMTd	*	*	*	0,0471	1,0000	1,0000	0,0229	0,5856	0,6818
SUTd	*	*	*	0,0081	*	*	0,0039	0,1027	*
CTd	*	*	*	*	*	*	*	*	*
PMTd	*	*	*	*	*	-0,8617	*	*	-0,4044

Note. The presence of a positive correlation implies a direct relationship between the input and the output: a positive sign (+) indicates a direct correlation (the KPI increases as the BD increases), while a negative sign (−) signals an inverse relationship (the KPI decreases as the BD increases, vice versa).

Factor Prioritization: The absolute values of the coefficients enable a strategic hierarchy of interventions. By quantifying the weight of each relationship, the manager can allocate technical resources to the “critical few” variables, those projected to yield the highest marginal improvement in performance.

Directional Steering: The algebraic sign of each coefficient guides operational adjustments regarding BD: a positive (+) correlation indicates that the base data and the KPI move in the same direction, while a negative (−) sign signals an inverse, ensuring that operational decisions are aligned with the desired performance outcomes. The “*” symbol indicates that there is no relationship between the variables and the corresponding KPIs.

This tool serves as the backbone for an interactive monitoring dashboard designed for the dynamic visualization of KPIs. It provides analytical support to managers in overseeing operational processes, facilitating alignment with predefined strategic objectives, and enabling the timely identification of key decision-making levers for performance improvement.

To illustrate an example of the utility of this framework, consider a scenario where management aims to reduce the system’s *Scrap Rate*. The decision-making process follows the three steps previously described:

Variable Identification: Upon examining the matrix column corresponding to the target KPI, that is *SR*, the manager identifies the set of influential input variables, which are *NCA*, *ND*, *RWQc*, and *SQd*.

Factor Prioritization: By evaluating the absolute values of the coefficients, the manager discerns that *SQd* represents the most significant lever, as it possesses the highest magnitude. This allows the concentration of resources on the variable that yields the greatest impact on *SR* reduction.

Directional Steering: Finally, the manager assesses the algebraic sign of the *SQd* coefficient. The presence of a positive correlation implies a direct relationship between the input and the output (that is between KPI and Base Data); therefore, to achieve the objective of reducing the *Scrap Rate*, the manager must implement a reduction in the *SQd* variable, ensuring the alignment between the tactical intervention and the desired performance outcome.

Alternatively, a **row-by-row analysis** evaluates the impact of each base data, mapping how a single variation propagates across multiple KPIs. This horizontal perspective reveals the **cascade effect** of operational changes, identifying the footprint of each input variable on the entire performance architecture. This view is particularly valuable for detecting structural trade-offs: it explicitly highlights where an intervention aimed at one metric may degrade another. By exposing these conflicting correlations, the SIM allows decision-makers to assess the net effect of any modification, ensuring that localized improvements do not compromise the overall process equilibrium.

Table 6. Intermediate linkage matrix (ILM): Section 1.

Variation (-)	SQc	CQc	PCQc	WRWQc	REc	VOTc	NVOTc	NOTc	OTc
NCA	-	+		+		+	-		
ND	-	+		+		+	-		
RWQc			-	+			-	-	-
FEc					-				
STUTc								-	
CMTc									
CTc									
PMTc									
SQd									
RWQd									
FEd									
STUTd									
CMTd									
SUTd									
CTd									
PMTd									

Note. The presence of a positive correlation implies a direct relationship between the input and the output: a positive sign (+) indicates a direct correlation (the KPI increases as the *BD* increases), while a negative sign (-) signals an inverse relationship (the KPI decreases as the *BD* increases, vice versa).

The second finding of this study represents a significant contribution to the existing literature, as it provides a detailed breakdown of the relationships between *BD* and KPIs as illustrated through the SIM framework. Specifically, the **Intermediate Linkage Matrix (ILM)** (Tables 6–8) clarifies the underlying links between *BD* and the *Intermediate Metrics* that determine the KPIs.

Furthermore, the ILM defines the nature of these dependencies: variations in Base Data are conventionally treated as reductions. Consequently, the algebraic sign in the matrix dictates the response of the intermediate metrics: a negative sign (-) indicates a direct correlation (the metric decreases as the *BD* decreases), while a positive sign (+) signals an inverse relationship (the metric increases as the *BD* decreases).

To clarify why a KPI might be influenced by a *BD* without a direct link, consider the *Quality Ratio - continuous system* (QR_c), defined as:

Table 7. Intermediate linkage matrix (ILM): Section 2.

Variation (-)	PBTc	POTc	PQd	SQd	RWQd	CQd	CQ	PCQd	QCFd
NCA			+	+	+	+	+	+	+
ND			+	+	+	+	+	+	+
RWQc	-	-							
FEc									
STUTc	-	-							
CMTc	-	-							
CTc		-							
PMTc		-							
SQd						+	+		
RWQd								-	+
FEd									
STUTd									
CMTd									
SUTd									
CTd									
PMTd									

Note. The presence of a positive correlation implies a direct relationship between the input and the output: a positive sign (+) indicates a direct correlation (the KPI increases as the *BD* increases), while a negative sign (-) signals an inverse relationship (the KPI decreases as the *BD* increases, vice versa).

Table 8. Intermediate linkage matrix (ILM): Section 3.

Variation (-)	PCQ	GQ	PPTd	REd	VOTd	NVOTd	NOTd	OTd	PBTd	POTd
NCA	+	+	+		+	+	+	+	+	+
ND	+	+	+		+	+	+	+	+	+
RWQc	-	+								
FEc										
STUTc										
CMTc										
CTc										
PMTc										
SQd		+			+	+				
RWQd	-	+				-	-	-	-	-
FEd				-						
STUTd								-	-	-
CMTd									-	-
SUTd									-	-
CTd										-
PMTd										-

Note. The presence of a positive correlation implies a direct relationship between the input and the output: a positive sign (+) indicates a direct correlation (the KPI increases as the *BD* increases), while a negative sign (-) signals an inverse relationship (the KPI decreases as the *BD* increases, vice versa).

$$QR_c = \frac{CQ_c}{CQ_c + SQ_c} \times 100 \quad (27)$$

Analysis of the SIM indicates that the variable *ND* impacts QR_c despite the lack of a direct functional correlation. The ILM resolves this by exposing the mediated path: a reduction in *ND* triggers an increase in the intermediate metric CQ_c and a decrease in the intermediate metric SQ_c . These variations in metrics, in turn, drives the variation in the final KPI (QR_c).

This further exploration of relationships bridges the gap between *BD*, intermediate metrics, and KPIs: it clarifies the causal chain by specifying how a *BD* influences a KPI, even in the absence of a direct correlation. By highlighting these mediated dependencies, the matrix provides a framework for understanding all factors that influence performance.

In conclusion, together these two matrices capture the full range of interrelationships within the system's performance framework. These tools are capable of capturing the cascading effects from base data to intermediate metrics and final KPIs, and vice versa, and of transforming static indicators into a dynamic map of dependencies. In this way, the manager gains a comprehensive understanding of how every single operational lever influences system performance. It is important to specify that the resulting matrices are strictly case-dependent and tailored to the modelled scenario and the illustrative data utilized; consequently, the derived coefficients are unique to this specific case study. The framework can subsequently be replicated and applied to other manufacturing systems to generate site-specific matrices reflecting different production processes.

7. Conclusion and future research

The present study introduced a multi-tier performance measurement framework specifically designed for pharmaceutical manufacturing environments. By developing the Sensitivity Impact Matrix and the Intermediate Linkage Matrix, this research has mapped the propagation of operational changes from Base Data through Intermediate Metrics to Key Performance Indicators. The proposed model provides system managers with a decision-support tool that identifies the critical levers for performance improvement, and clarifies the trade-offs and interrelations between Quality, Time, and Maintenance domains. The deterministic approach adopted for the sensitivity analysis ensures that every management intervention is grounded in the mathematical and physical logic of the system under examination.

Of course, certain limitations remain, which point to opportunities for future research.

First of all, currently, SIM and ILM function as deterministic sensitivity models. Progress would involve the integration of *stochastic simulations* (e.g., Monte Carlo methods⁵³) to account for the inherent variability and randomness of pharmaceutical processes. In this way, the predictive tool would enable the forecasting of KPIs across various uncertainty scenarios.

One limitation of this study concerns the specific nature of the context in which the numerical results are obtained. The coefficients and matrices obtained depend on the specific scenario modelled and the illustrative dataset used; therefore, they cannot be directly transferred or applied as universal reference parameters for every production system. However, the aim of

this work is to validate a generalized methodology rather than to provide absolute parameters. Consequently, a possible future research is to apply the multi-level framework to various industrial case studies and different production configurations. This will enable the scalability of the methodology.

Future studies could integrate environmental and social indicators, such as Energy Intensity, Carbon Footprint per Batch, or Water Utilization Effectiveness.⁵⁴ Given the high energy demands of pharmaceutical cleanrooms and Heating, Ventilation, and Air Conditioning systems,⁵⁵ correlating base production data with sustainability metrics would align the system's efficiency with global Green Manufacturing standards.⁵⁶

While the current KPIs focus on operational and physical performance, a significant evolution would involve mapping Base Data (BD) variations directly to financial outcomes. Introducing metrics like Cost of Poor Quality⁵⁷ or Total Cost of Maintenance per Unit would allow for a direct Cost-Benefit analysis of technical interventions.

Finally, this study paves the way for various methodological extensions. In particular, a promising line of research concerns the possibility of extending the analysis beyond BDs by directly integrating process parameters from the shop floor. One could investigate the relationships between production operating variables (such as temperatures, pressures, line speeds or mixing times) and BDs, i.e. study which operating parameters influence KPI values. Linking performance indicators to the intrinsic dynamics of production would allow efficiency to be monitored and predicted in real time, transforming the KPI into an active control parameter.

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Appendix

Nomenclature

A	Availability Rate
Ac	Availability Rate - continuous system
Ad	Availability Rate - discrete system
AEDTc	Actual Equipment Down Time - continuous system
AEDTd	Actual Equipment Down Time - discrete system
AENPTc	Actual Equipment No Processing Time - continuous system
AENPTd	Actual Equipment No Processing Time - discrete system
ANP	The Analytical Network Process
AT	Actual Throughput
ATc	Actual Throughput - continuous system
ATd	Actual Throughput - discrete system
BD	Base Data
C	Categories
CMR	Corrective Maintenance Ratio
CMRc	Corrective Maintenance Ratio - continuous system
CMRd	Corrective Maintenance Ratio - discrete system

CMTc	Corrective Maintenance Time - continuous system
CMTd	Corrective Maintenance Time - discrete system
CQ	Conforming Quantity
CQc	Conforming Quantity - continuous system
CQd	Conforming Quantity - discrete system
CTc	Cleaning Time - continuous system
CTd	Cleaning Time - discrete system
DEMATEL	The Decision-Making Trial and Evaluation Laboratory
DR	Deviation Ratio
FEc	Failure Event - continuous system
FEd	Failure Event - discrete system
FPY	First Pass Yield
FPYd	First Pass Yield - discrete system
FTQ	First Time Quality
GCP	Good Clinical Practices
GLP	Good Laboratory Practices
GMP	Good Manufacturing Practices
GQ	Good Quantity
ILM	Intermediate Linkage Matrix
ISM	Interpretative Structural Modeling
KPI	Key Performance Indicator
λ	Failure Rate
λ_c	Failure Rate - continuous system
λ_d	Failure Rate - discrete system
M	Maintenance
MIMIT	Ministero delle Imprese e del Made in Italy
MTBF	Mean Time Between Failure
MTBFc	Mean Time Between Failure - continuous system
MTBFd	Mean Time Between Failure - discrete system
MTTR	Mean Time To Repair
MTTRc	Mean Time To Repair - continuous system
MTTRd	Mean Time To Repair - discrete system
NCA	Number of Check Activities
ND	Number of Deviations
NOTc	Net Operating Time - continuous system
NOTd	Net Operating Time - discrete system
NPTc	No Processing Time - continuous system
NPTd	No Processing Time - discrete system
NVOTc	Non-Valuable Operating Time - continuous system
NVOTd	Non-Valuable Operating Time - discrete system
OEE	Overall Equipment Effectiveness
OPEX	Operational Excellence
OTc	Operating Time - continuous system
OTd	Operating Time - discrete system
P	Performance Efficiency
Pc	Performance Efficiency - continuous system
Pd	Performance Efficiency - discrete system
PBTc	Planned Busy Time - continuous system
PBTd	Planned Busy Time - discrete system
PCQ	Processed Quantity
PCQc	Processed Quantity - continuous system
PCQd	Processed Quantity - discrete system
PDTc	Planned Down Time - continuous system
PDTd	Planned Down Time - discrete system

PMTc	Preventive Maintenance Time - continuous system
PMTd	Preventive Maintenance Time - discrete system
PMTc	Preventive Maintenance Time - continuous system
PMTd	Preventive Maintenance Time - discrete system
POTc	Planned Operation Time - continuous system
POTd	Planned Operation Time - discrete system
PPTd	Planned Processing Time – discrete system
PQ	Produced Quantity
PQc	Produced Quantity - continuous system
PQd	Produced Quantity - discrete system
PT	Planned Throughput
PTc	Planned Throughput - continuous system
PTd	Planned Throughput - discrete system
Q	Quality
QA	Quality Assurance
QCFd	Quantity Compliant at First Time - discrete system
QR	Quality Ratio
QRc	Quality Ratio - continuous system
QRd	Quality Ratio - discrete system
REc	Repair Event - continuous system
REd	Repair Event - discrete system
RFc	Reference Time - continuous system
RFd	Reference Time - discrete system
RFT	Right First Time
RFTc	Right First Time - continuous system
RM	Raw Materials
RMd	Raw Materials - discrete system
RWR	Rework Ratio
RWRc	Rework Ratio - continuous system
RWRd	Rework Ratio - discrete system
RWQc	Rework Quantity - continuous system
RWQd	Rework Quantity - discrete system
RTc	Reference Time - continuous system
RTd	Reference Time - discrete system
SA	Sensitivity Analysis
SIM	Sensitivity Impact Matrix
SQc	Scrap Quantity - continuous system
SQd	Scrap Quantity - discrete system
SR	Scrap Ratio
SRc	Scrap Ratio - continuous system
SRd	Scrap Ratio - discrete system
STUTc	Startup Time - continuous system
STUTd	Startup Time - discrete system
SUTd	Setup Time - discrete system
T	Time
TBFc	Time Between Failure - continuous system
TBFd	Time Between Failure - discrete system
TRc	Throughput Rate - continuous system
TRd	Throughput Rate - discrete system
TTRc	Time To Repair - continuous system
TTRd	Time To Repair - discrete system
VOTc	Valuable Operating Time - continuous system
VOTd	Valuable Operating Time - discrete system
WRWQc	Without Rework Quantity - continuous system