A Work Project, presented as part of the requirements for the Award of a Master's degree in Business Analytics from the Nova School of Business and Economics.

# DATA EXCELLENCE IN OPERATIONS MANAGEMENT

## Enabling data-driven decision-making by developing a leadership dashboard at Quantum Systems

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**Abstract**

This work project designs and evaluates a leadership dashboard to support data-driven decision-making in Quantum Systems' Operations division. Guided by the research question "How can a leadership dashboard be designed to improve data insights in Operations management?", the project follows a three-step approach inspired by Design Science Research. It derives a KPI framework, assesses data readiness across core systems, and implements selected indicators in Power BI. Evaluation along four data pillars: Volume, Quality, Accessibility, and Governance, combines quantitative comparisons and stakeholder feedback, indicating reduced information overload and fragmentation, increased data trust and improved accessibility of operational information for leadership.

**Keywords**

Data-Driven Decision-Making; Operations Management; Key Performance Indicators (KPIs); Leadership Dashboard; Operations Analytics; Business Intelligence; Power BI

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# 1 Introduction

Organizations today operate in an environment where the volume of digital data is expanding at an unprecedented pace. The data produced and processed worldwide each year has risen from about 2 zettabytes in 2010 to roughly 173 zettabytes in 2024 and is forecasted to reach about 528 zettabytes by 2029 (Statista 2025). While this development creates the potential to gain deeper insights into operations, customers, and markets (Stach 2023), many firms still struggle to translate data availability into better decisions. Gartner (2018), for example, reports that 87% of organizations have low BI and analytics maturity, and a recent study by Drexel University LeBow College of Business and Precisely (2024) finds that although 77% of data analytics professionals name data-driven decision-making as their primary objective, 67% do not fully trust their organizational data. Fragmented system landscapes, inconsistent metric definitions, and low-quality or inaccessible data can thus cause data to shift from an asset to a burden. To realize its benefits, it must be accessible in a standardized way and at the right volume and quality (Dean and Webb 2011; Miller et al. 2024).

This work project is conducted in collaboration with Quantum Systems GmbH (QS), a rapidly growing drone manufacturer headquartered near Munich, Germany. Founded in 2015, QS develops and manufactures unmanned aerial systems for various applications and has experienced rapid scaling in revenue, production output, and workforce in recent years (Quantum Systems 2025a, 2025b). This growth has increased organizational complexity and made it more difficult for Operations leadership to maintain a consolidated overview of relevant information across teams, systems, and locations. QS therefore provides relevant context for investigating how a leadership dashboard and an associated KPI framework can address real-world data and information challenges in operations management.

## 2 Methodology

The guiding research question of this thesis is: “How can a leadership dashboard be designed to improve data insights in Operations management and support faster, more informed decision-making?” To address this question, a theoretical foundation was developed based on literature on data-driven decision-making, its challenges and best practices, key performance indicators (KPIs), and dashboard-based visualization. Building on these insights, the project followed a structured three-step approach inspired by Design Science Research (DSR) (Peffers et al. 2007). The three steps, Frame & Specify, Design & Build, and Evaluate, are mapped to the DSR process of problem identification, design and development, demonstration, and evaluation, as summarized in Figure 1.

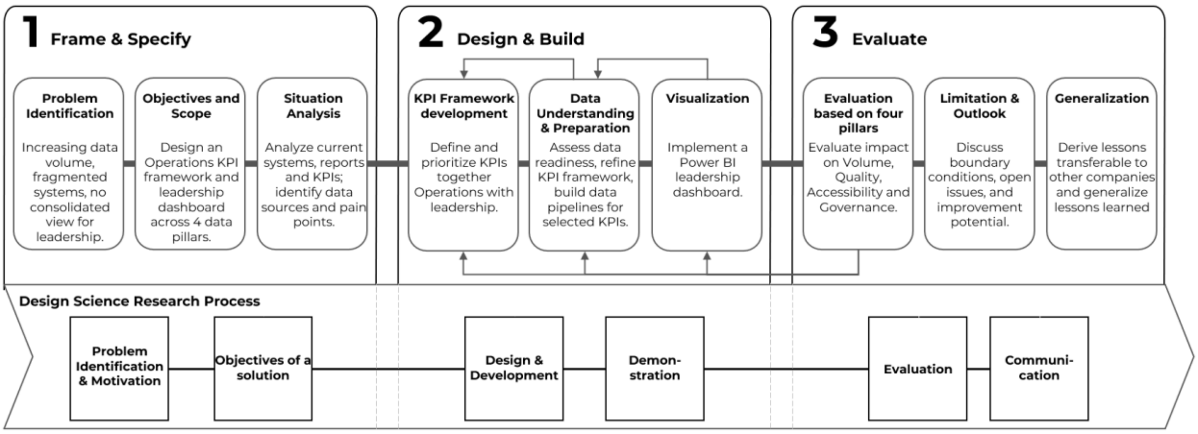


Figure 1 - Three-step approach and its mapping to DSR (Author’s own illustration)

**Frame & Specify:** In the first phase, the problem, objectives, and context were clarified through three main activities: problem identification, definition of objectives and scope, and a structured situation analysis (Sections 4.1-4.3). Problem identification combined on-site observations (at least half a day per team), informal discussions with team members, and one initial semi-structured interview each with the Director of Operations and the Head of Production. Based on these insights, a shared problem statement, objectives, and scope were defined. Building on this, a situation analysis was conducted that examined the organizational structure of the Operations division, the existing systems landscape, and current KPI reporting practices. Across these steps, the identified issues and objectives were grouped into four data pillars: Volume, Quality, Accessibility, and Governance, which provided a clear structure for the design requirements for the dashboard and the later evaluation.

**Design & Build:** In the second phase, an initial KPI framework was developed based on three working sessions with the Director of Operations (2x 60 min, 1x 90min). In line with QS' internal language, all indicators throughout the thesis are referred to as "KPIs", even though several would conceptually be classified as performance indicators in the terminology of Parmenter (2015). The initial framework was then refined through an iterative process of data understanding, preparation, and visualization using Python and Power BI, consistent with the iterative nature of DSR. Each indicator was evaluated along three criteria, derived from Parmenter's characteristics of 'winning KPIs' and from recent data-quality frameworks, adapted to QS' context (Miller et al. 2024; Parmenter 2015). **Strategic Relevance** – is the KPI linked to a strategic goal, and does it support clear managerial action? **Data Readiness** – Are the necessary data points available in sufficient quality? **Execution Feasibility** – Is the execution feasible with reasonable effort and costs? As shown in Figure 2, KPIs that did not satisfy these criteria were either deprioritized or added to a backlog.

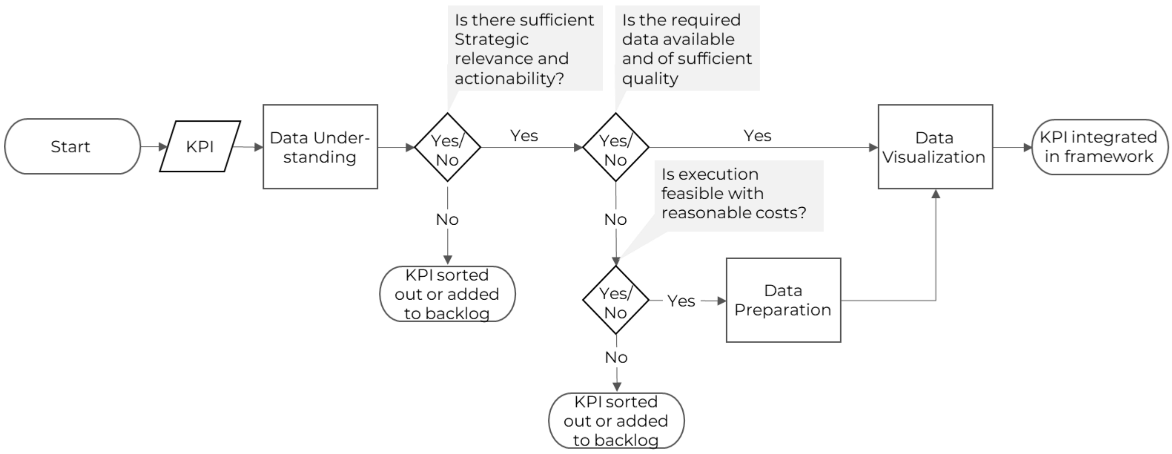


Figure 2 - KPI screening and implementation process (Author's own illustration)

Depending on data availability, different approaches were used for data understanding and preparation. For KPIs based on data already provided by the business intelligence (BI) team, data understanding was carried out directly in Power BI by exploring tables, creating test visuals, and comparing data with the source systems. If further data preparation was needed, it was also done with Power BI. Uncertainties were clarified together with the BI team or the respective team lead. For KPIs relying on data not yet provided by the BI team, data understanding was performed by accessing the relevant source systems and their APIs, analyzing the raw data in Python, and finally creating Python-based pipelines to retrieve and transform the data on a regular basis. The selected KPIs were then visualized in a leadership dashboard using Power BI. The design followed established dashboard best practices that have been identified in Section 3.4 to ensure that the final artifact is suited for leadership with limited time and no specialized analytics training.

**Evaluate:** In the third phase, the artifact was evaluated using a combination of quantitative and qualitative methods across the four data pillars: Volume, Quality, Accessibility, and Governance. Quantitative analysis compared selected indicators, such as the number of reports regularly consumed by Operations leadership and the number of distinct systems accessed for the same information, before and after the implementation of the artifact. Qualitative insights were derived from stakeholder feedback gathered through semi-structured interviews and informal discussions and were summarized thematically in structured notes. Table 1 summarizes the evaluation logic by linking each pillar to its corresponding objective and indicative evaluation criteria.

***Table 1*** – Evaluation across the four data pillars

| Pillar | Objective | Evaluation |
|---|---|---|
| **Volume** | Reduce information overload and provide only relevant data for Operations leadership. | Amount of noise* received decreases **(Qualitative)**<br>Number of reports consumed decreases **(Quantitative)** |

| | | |
|---|---|---|
| **Quality** | Ensure consistent and reliable data records to prevent misleading insights. | Confidence in available data rises **(Qualitative)**<br>Data quality of implemented KPIs is adequate for reliable analysis **(Quantitative)** |
| **Accessibility** | Improve stakeholder access to information and overcome siloed systems. | Information gathering is easier **(Qualitative)**<br>Number of distinct systems needed for the same information decreases **(Quantitative)** |
| **Governance** | Establish clear data ownership and reduce conflicting "sources of truth." | Management and leadership are aware of KPI ownership & accountability **(Qualitative)**<br>KPI catalogue is perceived as comprehensive, consistent and self-explanatory **(Qualitative)** |

*Irrelevant data distracting from insightful information

Empirical data for the Frame & Specify, Design & Build, and Evaluate phases was collected through semi-structured interviews, working sessions and non-participatory on-site observations with key stakeholders in Operations. Appendix I provides an overview of these activities and the underlying data-collection procedures.

# 3 Literature Review

## 3.1 Data-Driven Decision-Making

With organizations having to deal with an increasing amount of data, leveraging information effectively has become a key differentiator for successful organizations. Hence, data-driven decision-making, which refers to the systematic use of data and statistical analysis to inform decisions, rather than relying primarily on intuition, has emerged. While human judgement remains important, it is prone to cognitive biases and limited by its information-processing capacity (Thiess and Müller 2018). Research links data-driven decision-making to superior performance. Davenport (2006) describes in "competing on analytics" how firms that embed rigorous analysis into strategy and culture gain a competitive advantage. Empirical studies report that emphasizing data-driven decision processes correlates with productivity gains of around 3–7% at the enterprise level (Brynjolfsson et al. 2011; Müller et al. 2018, 26). More recent survey evidence shows that a strong big-data analytics capability and a data-driven culture jointly improve operational and financial performance (Karaboga et al. 2023).

However, these benefits materialize only when certain prevailing conditions are met. Recent work on data analytics capabilities highlights that value from analytics arises when organizations can combine three elements: high-quality data, an integrated data infrastructure, and data-related human resources (Gupta and George 2016; Madhala et al. 2022). Data must be accurate, consistent, and timely across systems to be trusted. Likewise, analytics and business-intelligence tools need to be integrated with operational systems and tailored to specific decision tasks, for example through dashboards that summarize key performance indicators. Moreover, realizing the potential of these business-intelligence tools requires data professionals to develop and maintain them, as well as managers with sufficient data literacy to interpret and act on the resulting insights (Müller et al. 2018; Park et al. 2016).

### 3.2 Challenges in the Effective Use of Data

Despite broad agreement on the value of data-driven decision-making, many organizations still struggle to translate available data into actionable insights. The literature highlights several recurring challenges that are particularly relevant for this work project.

**Information overload.** The expansion of available data increases the risk of information overload, a state of having more data than one can effectively process. Research shows that information overload can reduce decision accuracy and efficiency, as managers struggle to distinguish signal from noise and may experience "analysis paralysis" or resort to superficial heuristics instead of systematic evaluation (Eppler and Mengis 2004; Kashada et al. 2020). In practice, this implies that simply adding more data or more reports does not automatically improve decision quality. **Data quality deficiencies.** High-quality data is a prerequisite for reliable insights. ISO/IEC 25012 describes data quality along dimensions such as accuracy, completeness, consistency, credibility, timeliness, and accessibility (Guerra-García et al. 2023). Building on this, recent work extends these dimensions and emphasizes that an organization must also address aspects such as governance, interpretability and usefulness for decision-making (Miller et al. 2024). Deficiencies across these dimensions can lead to misleading insights or reduce trust in analytical outputs, ultimately leading managers to ignore reports. **Data silos and limited accessibility.** As organizations expand their application landscape, data often becomes fragmented across isolated systems or units. Such data silos make information hard to access and aggregate, requiring users to consult multiple systems for a single decision (DalleMule & Davenport 2017). These manual, time-consuming efforts delay obtaining an overall view of operations and worsen the overall user experience. Consolidating disparate sources into coherent data structures is therefore critical, but technically and organizationally demanding (Madhala et al. 2022; Müller et al. 2018). **Skills gaps and cultural barriers.** Even the best data strategy will fail if there is no enabling culture with skilled personnel utilizing the data for decision-making. To realize the potential, organizations require a workforce that can interpret and question data, ranging from specialists such as data analysts and engineers to managers with sufficient data literacy to understand basic analyses, challenge assumptions and translate insights into actions (Gupta & George 2016; Madhala et al. 2022). Many organizations lack staff who combine analytical skills with business knowledge, and managers often are not confident when working with data (Smith et al. 2019). A data-driven culture, where evidence is systematically considered in discussions, data is broadly accessible, and teams are held accountable for measurable outcomes, is therefore as important as the workforce itself (Karaboga et al. 2023). **Governance and ownership gaps.** Finally, recent data-quality frameworks explicitly include governance as a separate dimension, because ownership, standards and policies directly affect whether data remains accurate, consistent and up to date (Guerra-García et al. 2023; Miller et al. 2024). Poor governance leads to divergent definitions for core concepts such as “order”, “customer”, or “on-time delivery” and to multiple sources of truth. Parmenter (2015) accordingly stresses the importance of clear ownership and standardized definitions and calculation logics. Without sufficient governance, even technically correct dashboards are unlikely to maintain the trust of their users.

### 3.3 Key Performance Indicators (KPIs)

Organizations require mechanisms to cut through information overload and focus on the data that matters. KPIs help by translating strategic goals into a small set of critical measures that signal current and future success. Parmenter (2015) defines seven characteristics of “winning KPIs”: 1. Are nonfinancial (not expressed in money), 2. Are measured frequently, 3. Are acted on by senior management, 4. Are clearly defined and understood, 5. Have clear ownership and responsibility, 6. Are strategically relevant and 7. Encourage action (Parmenter 2015).

However, literature also highlights recurring pitfalls in KPI practice. First, organizations often label too many metrics as “key”, leading to dashboards with dozens of indicators without sufficient strategic relevance. Secondly, indicators are frequently chosen because data is available rather than because they reflect critical success factors. This can drive local optimization or dysfunctional behaviour (for example, improving one metric at the expense of another one). Third, KPIs are sometimes defined without clear formulas, data definitions or measurement frequency, resulting in inconsistent calculation across teams and undermining trust in the numbers (Parmenter, 2015).

### 3.4 KPI Reporting through Dashboards

Organizations increasingly implement KPI reporting through digital dashboards. In literature, dashboards are described as interactive visualization tools that collect, aggregate, and present data from various sources in one place, thereby supporting informed decision-making (Msibi et al. 2025; Yigitbasioglu and Velcu 2012). From a design perspective, authors distinguish between **visual** and **functional** features. Visual design concerns how information is displayed.

Effective dashboards typically follow a single-screen logic, presenting the most important information on one page so that key developments can be monitored at a glance. Most critical measures are placed in the foreground and highlighted (Msibi et al. 2025). Colors are used sparingly and purposefully and decorative elements are minimized. At the end, the “data-ink ratio” should be maximized, which means that as much information as possible should be displayed with the least number of elements (Yigitbasioglu and Velcu 2012). Functional features determine what users can do with the dashboard. Beyond static display, dashboards should enable interactive exploration through drill-down and filtering. In practice, drill-down capabilities allow users to deep dive into underlying dimensions (e.g. product, customer, time period) to identify root causes. In some cases, it is helpful to offer tabular views when exact values are needed for detailed judgements, while in other cases more superficial visualizations are the better choice (Yigitbasioglu and Velcu 2012).

# 4 Frame and Specify

## 4.1 Problem Identification

Quantum Systems is currently experiencing rapid growth in production output and supply chain activity. This expansion has been driven by a strong focus on execution and the leadership principle “speed over perfection”. While this mindset has enabled such rapid growth in the first place, it has also led to a systems and data landscape in Operations that has evolved organically rather than systematically. As a result, operational data is fragmented across these systems with varying levels of data quality. To obtain a consolidated picture, Operations leadership must manually extract information from several sources and consult various stakeholders. This situation poses several data-related risks, which were grouped into four practical pillars for use at Quantum Systems. These pillars are informed by data-quality dimensions in ISO/IEC 25012 and Parmenter’s work on “winning KPIs” but were deliberately adapted to the specific context and execution requirements of Quantum Systems (Guerra-García et al. 2023; Parmenter 2015). **Volume:** The large volume of available data makes it difficult to focus on only important things, and data collection takes an increasing amount of time. **Quality:** Some data is incomplete, outdated, or inconsistent and the current manual data collection processes are prone to errors. **Accessibility**: Relevant information is distributed across several systems and files, which requires significant effort to access and combine. While accessibility is not a separate dimension within ISO/IEC 25012 but is included as an aspect of data quality, it was deliberately introduced as its own pillar in this thesis, as it proved to be a particularly critical requirement for Operations leadership at Quantum Systems. **Governance:** There are no central naming conventions and definitions for KPIs, and ownership for specific metrics is not fully established, which has repeatedly led to inconsistent figures and discontinued tracking.

QS is aware of those challenges and has therefore established a centralized Business Intelligence (BI) team responsible for advancing data excellence initiatives across the organization. One of the BI Team's core OKRs is to "create a QS Group data catalogue to identify and document Single Sources of Truth (SSOTs)", represented in the development of a centralized database to act as foundation for analytics. However, this centralized approach also has structural limitations. As the organization continues to scale, the BI team becomes increasingly detached from daily operations, while the operations data increases in complexity and processes change continuously. This creates a gap between business expertise and data knowledge, which this work project seeks to narrow by designing and evaluating an Operations leadership dashboard and KPI framework grounded in the day-to-day context of QS.

### 4.2 Objectives and Scope

**Objectives:** The primary purpose of this work project is to develop a digital artifact, consisting of two components: (1) a KPI framework documented in Confluence (2) a leadership dashboard built in Power BI, calculating and visualizing the defined KPIs. The objectives are set along the four pillars defined in Section 4.1: **Volume:** Reduce information overload and provide only relevant data for Operations leadership. **Quality:** Ensure consistent and reliable data records to prevent misleading insights. **Accessibility:** Improve stakeholder access to information and overcome siloed systems. **Governance:** Establish clear data ownership and reduce conflicting sources of truth. The dashboard visualizes the KPIs defined in the KPI framework and integrates data from different systems. It will act as "single source of truth" in which the status of each KPI is available for decision-makers. By aggregating and visualizing these data points, the dashboard is intended to support more data-driven decision-making.

**Scope**: While there are other important enablers of data excellence, such as organizational culture and skill level of personnel, these aspects are not directly addressed by the artifact and therefore lie outside the objectives of this work. The project is deliberately scoped to the needs of Quantum Systems' German Operations division, including the departments Production and Supply Chain Management. Operations was chosen as the focus because it lies at the center of many information flows, from supply chain and production metrics to project management and resource allocation, and because scaling production capabilities is currently one of the company's central challenges. Focusing on a single domain enables the development of a KPI framework that closely aligns with processes, data sources, and stakeholder needs and ensures that the project remains feasible within the time and resource constraints of this work.

### 4.3 Situation Analysis

The Operations division currently consists of about 100 employees, led by Alexandra M.E. Rietenbach, Director of Operations. Reporting directly to her are a project manager, a master's thesis student, the Operational Excellence team, the Production department and the Supply Chain Management department. Within Production there are four further teams and three individual contributors, together accounting for around 60 employees. Supply Chain Management comprises three teams, totaling in approximately 30 employees. The Operational Excellence team and the Production 2 team are excluded from the scope of this work.

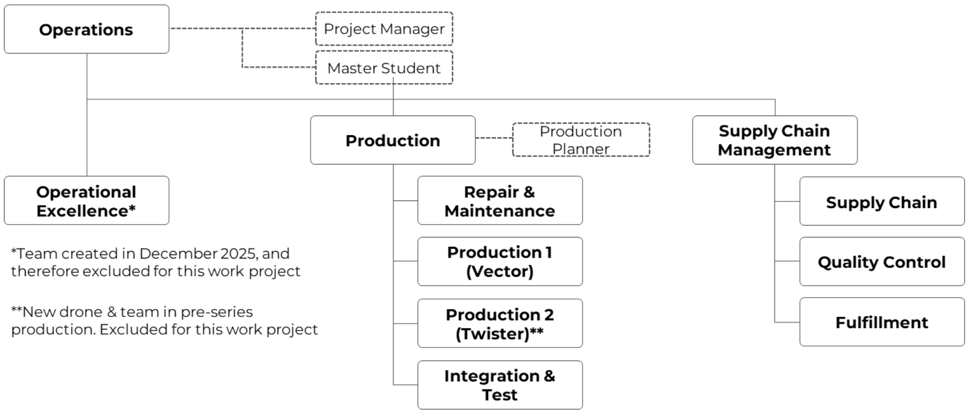


Figure 3 - Organizational structure of the Operations division at Quantum Systems

**Systems landscape & data flow:** As explained in Section 4.1, the systems landscape has become increasingly complex, leading to a variety of redundant systems and inconsistent data collection. Currently, the Operations department uses 10 distinct systems, as shown in Table 2.

Table 2 - Overview of all systems currently in use within Operations

| Name | Company | Function | Relevance for the thesis |
|---|---|---|---|
| **NetSuite** | Oracle | ERP | Serves as the primary source of production and supply data for KPI calculations. |
| **RF Smart** | RF Smart | WMS | Supports warehouse execution via mobile scanning; operational data is stored in NetSuite (used mainly for process understanding). |
| **Sloth** | In-house creation | PLM | Provides product definitions, identifiers, and component structures that supply context for KPIs. |
| **Operations1** | Operations1 | Work Instructions | Hosts digital work instructions and production planning; provides process step-time and production output data. |
| **Redmine** | Open-Source Software | Ticketing | Legacy system to be discontinued by end-2025; retains historical defects, rework, and maintenance records. |
| **Jira** | Atlassian | Ticketing & PM | Replaces Redmine for ticketing and supports project-management workflows. |
| **Confluence** | Atlassian | Collaboration & Documentation | Serves as the collaboration and documentation space (processes, projects, handbooks); PMBD processes migrate here; used to document KPI details. |
| **PMBD** | In-house creation | Process Management Documentation | Legacy repository to be decommissioned by end-2025; holds detailed process descriptions (no KPI data) but aids data understanding. |

| | | | |
|---|---|---|---|
| **Personio** | Personio | Human Resources | HR system for employee data such as FTEs, sick days, vacation, home office or team structures. |
| **Microsoft 365** | Microsoft | Collaboration | Enables communications and file storage (Teams/ SharePoint) and provides Excel, PowerPoint, and Word. |
| **Power BI** | Microsoft | Analytics / BI | Used by leadership for company-wide, non-Operations-specific reports; in this work, Power BI is introduced as the KPI reporting tool for Operations as part of the artifact. |

**Established KPIs:** Within Operations, there are currently nine KPIs tracked regularly. Except for "Confirmed vs actual ship date", "On-time delivery rate", and "Planned vs actual Output", none of these is retrieved automatically from systems. Furthermore, "Planned vs actual Output" is tracked twice, once automatically via NetSuite and once on the Shopfloor board in the production area. Both report different values because they represent different KPIs that share the same name. The NetSuite measure counts drones that are fully produced, have passed all checks (including quality control), and have been booked into NetSuite as finished products. The value on the Shopfloor board describes assembled drones, before they go through the final check, quality control and before they are booked into NetSuite. In addition, over time many further KPIs have been introduced, tracked for a limited period and then discontinued or retrieved manually on demand. Examples include workforce and time-recording metrics such as workforce per product (planned hours, actual hours, Saturday working hours) or supply chain metrics such as number of qualified A suppliers.

# 5 Design and Build

## 5.1 KPI Framework development

The starting point for the KPI framework was the existing, heterogeneous set of nine KPIs currently tracked in Operations. Building on these indicators and on qualitative insights from observations and interviews, three working sessions with the Director of Operations were conducted to develop an initial KPI framework. This process yielded an intentionally broad longlist of 37 KPIs (see Appendix IV). For each KPI, the documentation specifies the attributes required to meet Parmenter (2015) characteristics of ‘winning KPIs’ (Section 3.3), including the definition, responsible team and owner, target value, measurement interval, and detailed calculation formula (see Figure 4 for an excerpt).

2.5.3 Average Repair Assessment Duration

By Lukas Stark  Status  1 min  Add a reaction

1. Basics

| | |
|---|---|
| **KPI Name** | Repair Assessment Duration |
| **Team** | Repair & Maintenance |
| **Owner** | [redacted] |
| **KPI-ID** | 2.5.3 |
| **Short Description** | Measures the time between initial support request and completion of evaluation |
| **KPI-Goal** | Minimize delays in diagnosis and response to ensure quick repair planning |
| **Unit** | Days per unit |
| **Target Value** | [redacted] |
| **Measurement Interval** | Monthly |
| **Comment** | KPI added to framework |

2. Calculation

| | |
|---|---|
| **Formula** | Average (Evaluation Date – Initial Support Request Date) |

2. Calculation

| | |
|---|---|
| **Formula** | Average (Evaluation Date – Initial Support Request Date)<br>Average time (in hours) between:<br>• **Starting Point:** Jira status changes to **“Request Repair”**<br>• **Ending Point:**<br>◦ status changes to **“Pending Customer Approval”** (if a quote is sent to the customer), **or**<br>◦ status changes to **“Repair in Progress”** (if QS covers the repair cost). |
| Filter | Only tickets that reach one of these two end statuses within the selected reporting period are included. |
| **Data Source(s)** | Jira API, Repair Ticketing Space |
| **Example** | **Example (Single Ticket)**<br>• **Start:** 13/07/2025 13:27 → “Request Repair”<br>• **End:** 16/07/2025 15:13 → “Pending Customer Approval”<br>• **Repair Assessment Duration: 73.77 h**<br>**Example (Average Across Period)**<br>Given three tickets with durations: 73.77 h, 48.25 h, 95.50 h<br>**Average Repair Assessment Duration:**<br>(73.77+48.25+95.50)/3=72.51 h |

3. Additional Comments

- Repair Ticketing in Jira was introduced in May 2025, previously it was tracked in Redmine. KPI will be available beginnend of June 2025. Previous data has to be extracted manually from Redmine.

Figure 4 - Excerpt from KPI framework documented in Confluence

The subsequent Data Understanding & Preparation phase, applying the screening approach described in Section 2 Methodology, was used to refine this initial version and derive the final KPI framework that forms the basis for the leadership dashboard.

## 5.2 Data Understanding & Preparation

In parallel to refining the KPI framework, a data-understanding and preparation process was carried out to reduce the initial KPI framework down to a more concise, implementable framework. This process was guided by the three screening criteria Strategic Relevance, Data Readiness, and Execution Feasibility, as described in the KPI screening process in Figure 2.

The central QS Group data catalogue, maintained by the BI team, already integrates data from several core systems, most notably NetSuite (ERP, production and supply-chain data), Personio (HR data), and Jira (existing pipeline for data from other divisions). Operations1 (production data) and the operations-relevant Jira ticketing systems for repair, maintenance and rework were not yet integrated at the start of the project. For each KPI on the longlist, the required data elements were mapped to these sources to determine which metrics could be calculated directly and where gaps remained, as summarized in Table 3.

***Table 3*** – Final KPI framework mapped to source systems

| System | Final KPIs | Data Collection |
|---|---|---|
| **NetSuite** | Supplier On-Time Delivery Rate, On-Time Delivery Rate (Customer), On-Time Delivery Rate (Intercompany), Shipping Cost Ratio, Completed Shipments | Data available in QS Group data catalogue; final data preparation in Power BI. |
| **Personio** | Sickness Rate, Turnover Rate, Average Tenure, Output per FTE | Data available in QS Group data catalogue; final data preparation in Power BI. |
| **Jira** | Average Repair Time, Repair Assessment Duration | Data pipeline existed, but required data was not included; requirements defined and communicated; pipeline adjusted by internal data scientist. |
| **Operations1** | Production Output, Output per FTE, Rework Rate, Maiden First Pass Yield, | Daily API pipeline developed; processes in production and Operations1 adjusted to provide required data. |
| **Excel** | Inbound Defect Rate, Outbound Defect Rate, Supplier PPM | KPIs not yet suitable for automated tracking but sufficient relevant; stable, protected, and query-ready Excel file created or adapted. |

As shown in Table 3, for NetSuite and Personio only limited preparation was necessary. The main tasks consisted of understanding the relevant fields, checking data quality, and aggregating records in Power BI to compute the final indicators.

For Jira, a data pipeline already existed, but the required fields for the KPIs “Average Repair Time” and “Repair Assessment Duration” were not included. The requirements for these KPIs were specified in collaboration with the Team Lead Repair & Maintenance and then formalized as a data-integration request for the internal data scientist (see Appendix V).

Production-related KPIs required more substantial integration work, as no export pipeline from Operations1 to the QS Group data catalogue existed initially. Both the underlying process and the data integration were adapted. On the process side, work instructions in Operations1 have been adjusted. For instance, the Postflight Check, a process step after the initial test flight of the drone, was extended with a mandatory field in which the operator records on which attempt (first, second, or third) the aircraft passed the test flight, providing the basis for the Maiden First Pass Yield KPI. On the technical side, a Python-based toolkit was developed that connects to the Operations1 REST API and exports the relevant entities into JSON tables daily. A final script combines tables to a concise table optimized for analytics. At the time of writing, the scripts are executed manually once per day. In the next step, they will be integrated by the data scientist into the standard BI data pipeline. The detailed script layout and output tables are documented in Appendix VI.

Based on these activities, the initial KPI longlist was screened along the three criteria and sequentially shortened. Detailed KPI-level decisions, including individual rationales for exclusion, are provided in Appendix VII.

## 5.3 Visualization using Power BI

Based on the refined KPI framework and the prepared datasets, the reporting solution was implemented in Microsoft Power BI, while remaining consistent with the design principles outlined in Section 3.4. Interim dashboard drafts were regularly reviewed with Operations leadership and iteratively refined to ensure that the visuals were intuitive and that the analyses addressed their decision needs. The final artifact consists of one leadership dashboard and several function-specific report pages, all built on a shared data model.

The dashboard is implemented as a single Power BI page structured in five sections: People & Organization, Production, Repair & Maintenance, Purchasing & Quality Control, and Fulfillment & Warehouse. Sections combine KPI cards with a small number of line or bar charts. For instance, the People & Organization area displays Sickness Rate, Turnover Rate and Tenure as cards, while Production shows Output per FTE and Maiden Flight First Pass Yield with a weekly production-output bar chart. Repair & Maintenance lead-time KPIs are shown together with monthly trends, Purchasing & Quality Control combines defect-rate KPIs with a cumulative defect-rate chart. Fulfillment & Warehouse show on-time delivery KPIs alongside a weekly on-time-delivery chart and total shipments. A dark background, limited color palette and consistent typography emphasize the values themselves, red and green indicate under- or over-performance against targets, whereas neutral tones are used for context. The first two sections are shown in Figure 5, the full dashboard is in Appendix VII.

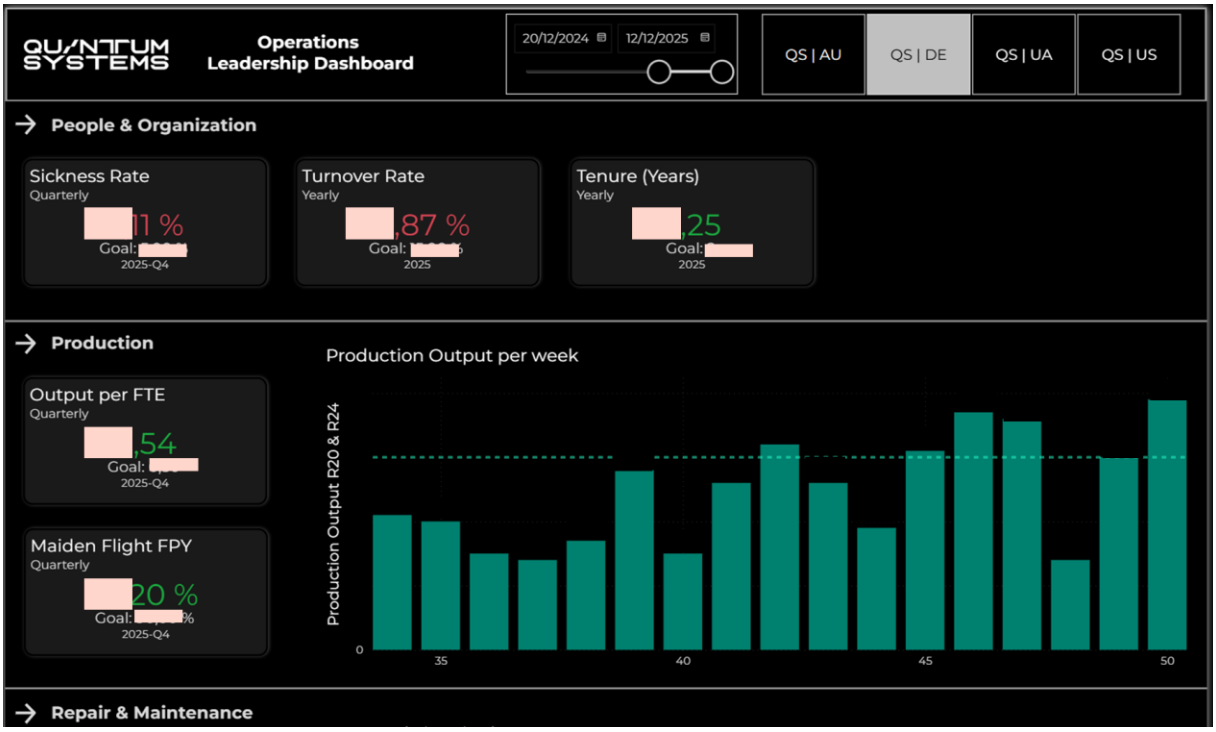


Figure 5 – Excerpt of the Operations leadership dashboard in Power BI (People & Organization and Production KPIs; values anonymized).

Global slicers at the top of the page allow leadership to filter by period and by site (e.g. QS-DE, QS-AU). Currently, the analytics are limited to the German site, which is why the filter is auto selected and not adjustable. The date slicer affects all visualizations but is particularly relevant at the deep dive sections. These slicers apply consistently across all visuals and all report pages. Selecting cards or chart elements triggers cross-filtering, making it possible to focus on a specific site, period or KPI without leaving the current view.

In addition to the leadership page, dedicated deep-dive reports provide “details on demand” for major indicators. The Repair & Maintenance page (Appendix IX), for instance, complements the lead-time cards with a monthly trend line, a matrix comparing quarters and months with the previous period, and a boxplot showing the distribution of individual ticket lead times, alongside cards for the number of repair and repair-assessment tickets.

All dashboards and reports use a shared semantic model in Power BI. Data from the QS Group data catalogue and the additional Jira and Operations1 pipelines is loaded and transformed in Power Query; KPI definitions and business rules are implemented as DAX measures so that each indicator is calculated consistently across all pages. Manually maintained Excel-based KPIs are integrated as protected data sources within the same model. Data refresh follows the cadence of the underlying pipelines (daily for Operations1 and Jira, and according to BI-team schedules for NetSuite and Personio), ensuring that all users work with a single, up-to-date version of the truth.

# 6 Evaluate

## 6.1 Evaluation based on four pillars

In line with the evaluation logic defined in Section 2 and Table 1, the artifact was evaluated along the four data pillars Volume, Quality, Accessibility, and Governance. The assessment combined (i) quantitative indicators (e.g. number of reports, systems, or KPIs used) with (ii) qualitative evidence from stakeholder interviews and informal feedback. The focus was not only on whether the leadership dashboard and supporting reports were technically implemented, but also on whether they addressed the underlying problems identified in the Frame & Specify phase. The following subsections summarize the evaluation results for each pillar. Table 9 in Appendix X summarizes the main evaluation results across the four pillars, and the following subsections provide more detailed discussion for each pillar.

**Volume objective:** Reduce information overload and provide only relevant data by focusing on (i) whether the perceived "noise" in reporting decreased, and (ii) whether the number of reports consumed in recurring leadership meetings shrank.

Before the project, Operations leadership relied on a fragmented mix of source-system views (primarily NetSuite and Operations1) and manually maintained Excel sheets. These views were not optimized for leadership-level reporting and often contained more detail than needed, while other relevant metrics were not tracked or were compiled ad hoc without standardization. With the new solution, 14 KPIs are consolidated in a single leadership view. Stakeholder feedback indicates that information overload decreased, as interviewees stated that the dashboard "saves time and gives a better overview." Quantitatively, the number of distinct reports used for regular performance discussions decreased for the topics covered by the current KPI framework: for these areas, leadership moved from several NetSuite reports and Excel sheets to primarily the Power BI dashboard.

**Quality objective:** Ensure consistent and reliable data records to prevent misleading insights. The evaluation focused on two aspects: (i) whether confidence in the available data rose among leadership and data owners, and (ii) whether the data quality of implemented KPIs is adequate for reliable analysis.

For the second aspect, sample checks were conducted by comparing selected KPI values in Power BI with their source systems and with ad hoc reports. Where discrepancies were identified during the build phase, definitions and transformations were adjusted before the final evaluation. Nevertheless, not all data is fully consistent or historically complete. For instance, some employees were initially assigned to incorrect teams in Personio, skewing KPIs such as Sickness Rate or Output per FTE. Furthermore, certain KPIs (such as Maiden Flight First Pass Yield or repair-related metrics from Jira) lack complete historical data because relevant processes and fields were introduced only recently. At the time of evaluation, 10 of the 14 final KPIs had sufficient data quality for both historical and current analysis. The remaining four KPIs (Output per FTE, Sickness Rate, Turnover Rate, Maiden Flight First Pass Yield) are expected to have adequate quality going forward, but with limited historical coverage. Qualitative feedback from Operations leadership and team leads indicates that trust in the reported KPIs has increased compared to the situation before. Stakeholders emphasized that clear, documented definitions in the KPI framework reduced ambiguity.

**Accessibility objective:** The Accessibility objective was to make information gathering easier and to reduce the number of distinct systems needed for the same information. Previously, Operations leadership often had to log into multiple tools (NetSuite, Personio, Jira, Operations1) and consult several NetSuite reports and Excel files to obtain a consolidated view. This was time-consuming and made it difficult to maintain a consistent picture across teams. Before the project, leadership typically accessed around five different systems and roughly ten separate reports to gather KPI data.

After the introduction of the Power BI solution, Excel is no longer used for accessing the KPIs included in the framework, and some NetSuite reports and the physical shopfloor board for production output have been replaced by the dashboard. This shift was confirmed by feedback from the Director of Operations, the Head of Production and the Head of Supply Chain Management. While current usage is limited to the KPIs already implemented, interviewees expect that Accessibility will improve further as the framework is expanded.

**Governance objective:** The Governance objective was to ensure that management and leadership are aware of KPI ownership and accountability, and that the KPI catalogue is perceived as comprehensive, consistent and self-explanatory for the current scope. Before the project, KPI definitions and calculation rules were not centrally documented, and measurement intervals were not standardized, increasing the risk that different teams would calculate the same indicator differently or rely on parallel, conflicting versions of KPIs.

The KPI framework in Confluence was used to assign an owner to each KPI. In interviews, leadership and team leads were asked who is responsible for specific KPIs and where definitions can be found. Out of 11 KPI owners, 9 were aware of their ownership and of the documentation, indicating a substantial improvement but also some remaining communication gaps.

Respondents generally viewed the KPI catalogue as comprehensive for the current scope. The dashboard itself was not yet perceived as fully comprehensive, because several important indicators, e.g. Warehouse and rework, are still missing. However, interviewees expressed a positive outlook and considered the current dashboard a solid first version that already consolidates several critical KPIs and provides a basis for future extensions.

### 6.2 Limitation & Outlook

This work provides a first, pragmatic step towards more data-driven operations management at QS, but it does not in itself create "data excellence". The dashboard has so far been used mainly in review sessions and prototype walkthroughs. Systematic evaluation in day-to-day operational still needs to be done. The empirical evaluation is therefore based on limited usage and a small number of interviews rather than on long-term behavioral data.

A second limitation concerns data readiness. Although some KPIs and reports existed prior to the project, they were largely maintained manually and lacked an overarching structure. As a result, considerably more effort than anticipated was required to reconcile definitions, clean source data and stabilize pipelines, and the project shifted more towards KPI framework design and KPI definition than initially planned.

As defined in the scope of this thesis, cultural aspects and data skills in Operations were not analyzed systematically. However, both the literature review and the experiences during this work project indicate that they are critical enablers of data-driven decision-making. Initial observations suggest that QS is relatively well positioned in this regard, with a central OKR on data excellence, a capable BI team, and strong intrinsic interest in data within Operations, but these factors were not evaluated in a structured way and therefore remain outside the formal results of this thesis.

Looking ahead, the Operations division now has a comprehensive KPI framework, a semantic data model and an initial leadership dashboard that can be extended over time. Future iterations should gradually integrate additional KPIs, refine existing visuals, and embed the dashboard more firmly into recurring management routines. In a subsequent step, the framework and dashboard could be internationalized and rolled out to other QS sites, adapting KPIs and data integrations to local processes while maintaining a consistent group-wide view. In line with the discussion in Section 3.3, it is recommended to complement the broader KPI set with a very small number of "true" key performance indicators that directly reflect the core operational challenge and receive extra focus. From today's perspective, promising indicators are Production Output versus Planned Output, On-Time Delivery, and Material Availability, as QS's Operations division main challenge in the coming years will be to scale production while reliably securing critical components on time. Responsibility for further improvement should lie with the Operational Excellence team in close collaboration with the BI team, with Operations leadership remaining the primary users and sponsors. The Operational Excellence team contributes deep process knowledge, ensuring that KPIs and dashboards reflect real operational needs, while the BI team provides scalable data integration and analytics capabilities. Through such iterative refinement, data quality can be stabilized further, and the solution can evolve in step with changing processes and information needs.

## 6.3 Generalization

This work is rooted in the specific case of Quantum Systems' Operations division, but several elements can be transferred to other contexts. In line with Design Science Research, the dashboard and KPI framework are not meant for statistical generalization, but rather, they offer a blueprint and design principles for similar initiatives (Peffers et al. 2007).

Within Quantum Systems, the KPI catalogue, Confluence documentation and Power BI dashboard can be extended to further sites and functions. The structure with clustered KPI groups and deep-dive pages, as well as the standardised KPI template, can be reused while adapting indicators, thresholds and data sources.

Beyond QS, several aspects appear generalizable. Defining a small number of data pillars and systematically mapping problems and objectives to them can provide a pragmatic lens to structure data issues and evaluate improvements. However, these pillars should not be treated as universal template, as they are suited to QS' specific context. An organization has to define its own pillars specific to the situation. Second, a screening logic that combines Strategic Relevance, Data Readiness and Execution Feasibility offers a practical way to reduce long KPI lists to a manageable leadership set. Third, a governance setup in which a central BI team provides the infrastructure while Operations co-owns KPI definitions and dashboard requirements can help to narrow the gap between technical data work and day-to-day decision-making.

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# 8 Appendix

## I. Overview of empirical data collection

## II. Table 4 - Overview of empirical data collection activities

| Type | Participants | Phase & Topic | Duration |
|---|---|---|---|
| **2x Semi-structured interview** | Director of Operations, Interim Head of Production | Frame & Specify – understanding current challenges in Operations | 90 min, 60 min |
| **Non-participatory observations** | All Operations teams | Frame & Specify – on-site observation of processes and information flows (min. ½ day per team) | ~ 5 days |
| **3x Working sessions** | Director of Operations | Design & Build – development of initial KPI framework | 2x 60 min, 90 min |
| **3x Semi-structured interview** | Director of Operations, Head of Production & Head of Supply Chain Management | Evaluate – perception of leadership dashboard and KPI framework | 3x 45 min |

### Semi-Structured interviews – Frame & Specify

The initial semi-structured interviews with the Director of Operations and the Interim Head of Production were conducted in the Frame & Specify phase to explore the problem space in an open manner. They focused on current operational challenges, existing reporting practices, and data-related pain points, as well as expectations for a leadership dashboard.

Main Topics

- Current operational challenges and priorities in Operations
- Existing KPIs and reports used for steering
- Data-related challenges (information overload, data quality, trust, accessibility, ownership)
- Expectations towards a leadership dashboard and desired insights

Example Guiding Questions

- Which reports or numbers do you currently look at to understand how Operations is performing?
- What KPIs are currently defined and tracked, and how?
- Where do you see the biggest gaps or weaknesses in today's reporting?
- Do you feel more overwhelmed by the amount of data, or constrained by missing information?
- How would you describe the main data-related challenges: quality, accessibility, trust, or unclear responsibilities?
- If you had one dashboard for Operations, what would you expect to see on it?

**Working sessions – Design & Build**

Three working sessions with the Director of Operations were conducted as interactive work meetings to co-develop the KPI framework. The focus was on identifying relevant indicators.

**Typical activities**

- Recap of the current KPI framework and discussion of changes since the previous session
- Clustering and prioritisation of KPIs by strategic importance and ownership
- Discussion of data availability, calculation logic, and feasibility for selected KPIs
- Agreement on next design steps and open questions for BI and Operations teams

These sessions were documented with structured notes capturing decisions on KPI inclusion, definitions and visualization requirements.

**Semi-structured interviews – Evaluate**

The final semi-structured interviews with the Director of Operations, the Head of Production and the Head of Supply Chain Management were conducted to evaluate the artifact along the four data pillars Volume, Quality, Accessibility and Governance. A common interview guide was used for all three stakeholders.

**Main topics and example questions**

- **Volume (information overload)**
  - Compared to the previous situation, do you feel that the amount of reporting ‘noise’ has decreased?
  - For your regular leadership meetings, which reports do you now use, and how has this changed?
- **Quality (trust and consistency of data)**
  - How confident are you in the correctness and consistency of the KPIs shown in the dashboard?
  - Have there been situations where numbers in the dashboard contradicted other sources? How did you handle this?
- **Accessibility (ease of access, number of systems)**
  - How has the effort to gather the information you need for decision-making changed?
  - Which systems and reports do you still need to open regularly in addition to the Power BI dashboard?
- **Governance (ownership and clarity of definitions)**
  - For the KPIs you use, is it clear to you who owns them and who is accountable for their values?
  - Do you know where to find the formal KPI definitions and calculation rules? Are they understandable?

Responses were documented in structured notes and later synthesised along the four pillars for the evaluation in Section 6.1.

### III. Table 5 - Overview of KPIs within Operations

| KPI | Description | Tracking |
|---|---|---|
| **On-time delivery rate** | Share of products delivered within the promised delivery time. | Automated via NetSuite |
| **Incoming goods defect rate** | Defect rate in incoming inspection. | Manually via Excel |
| **Crashes per flight hour** | Ratio of crashes to total flight hours. | Manually via Excel |
| **Outgoing goods error rate** | Error rate in outbound processes (shipping / fulfillment). | Manually via Excel |
| **Maiden flight success rate** | Number of OK/NOK maiden flights and resulting success rate. | Manually via Excel |
| **Repair assessment cycle time** | Average time from support request to feedback from repair (days per unit). | Manually via Excel |
| **Repair cycle time** | Time from customer clearance to handover back to support (days per unit). | Manually via Excel |
| **Planned vs actual output (tracked twice)** | Comparison of planned and actual production output, mainly tracked on the shopfloor. | Automated via NetSuite & Manually via Shopfloor |
| **Confirmed ship date vs actual ship date** | Average delay between confirmed and actual shipment date. | Automated via NetSuite |

### IV. Table 6 - Initial KPI Framework (37 KPIs)

| # | KPI Name | Team | Owner | Short Description | Target Value | Interval | Unit |
|---|---|---|---|---|---|---|---|
| **1.1** | Revenue per Operations Hour | Operations | Conf. | Operative Revenue per worked hour (only operations staff) | Conf. | Monthly | € / hour |
| **1.2** | Absence Rate | Operations | Conf. | Percentage of workdays lost due to sickness-related absence | Conf. | Monthly | % |
| **1.3** | Home Office Rate | Operations | Conf. | Average percentage of working days performed remotely among home office eligible employees. | Conf. | Monthly | % |
| **1.4** | Turnover Rate | Operations | Conf. | Measures the percentage of employees leaving the company within a specific time frame. | Conf. | Quarterly | % (Percentage) |
| **1.5** | Average Tenure | Operations | Conf. | Shows the average length of time current employees have been with the company. | Conf. | Yearly | Years |
| **2.1.1** | Output per FTE | Head of Production | Conf. | Number of total produced units per FTE | Conf. | Monthly | Units / Hour |
| **2.1.2** | Revenue per Production Hour | Head of Production | Conf. | Average revenue generated per productive hour worked by production staff. | Conf. | Monthly | € / Hour |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **2.1.3** | Cycle Time | Head of Production | Conf. | Measures the average cycle time for a certain component (Main, Payload, subprocess, product/revision) | Conf. | Weekly | Hours |
| **2.2.1** | Schedule Adherence | Production Planning | Conf. | Percentage of production orders that are completed on schedule. | Conf. | Weekly | % |
| **2.2.2** | Work Orders per Production Planner | Production Planning | Conf. | Number of work orders processed per production planner per week. | Conf. | Weekly | Work Orders / FTE / Week |
| **2.3.1** | Production Output | Production – Main Products & Rework | Conf. | Comparison of planned production output with the actual achieved output. | Conf. | Weekly | % (Actual / Planned) |
| **2.3.2** | Rework Rate | Production – Main Products & Rework | Conf. | Percentage of parts requiring rework after initial production. | Conf. | Monthly | % |
| **2.3.3** | Labor Utilization Rate (OEE) | Production – Main Products & Rework | Conf. | Measures the productive time of staff directly working in production processes. | Conf. | Monthly | % |
| **2.3.4** | Top 5 Rework Topics | Production – Main Products & Rework | Conf. | Most frequent causes for rework. | Conf. | Monthly | Count (optional: minutes/hours) |
| **2.4.1** | Maiden Flight First Pass Yield | Pre-Assembly & Testing | Conf. | Share of Vectors passing first test flight without rework. | Conf. | Monthly | % |
| **2.5.1** | Average Repair Duration | Repair & Maintenance | Conf. | Avg. time from customer approval to repair handover; segmented by effort category. | Conf. | Monthly | Days per unit |
| **2.5.2** | Internal vs External Workload Distribution | Repair & Maintenance | Conf. | Compares time spent on internal vs external repair tasks. | Conf. | Monthly | % internal / % external (hours) |
| **2.5.3** | Repair Assessment Duration | Repair & Maintenance | Conf. | Time from support request to evaluation completion. | Conf. | Monthly | Days per unit |
| **3.1.1** | Blocked Inventory Ratio | Supply Chain Management | Conf. | Share of inventory value currently blocked vs total. | Conf. | Monthly | % |
| **3.1.2** | Open & Closed Change Requests | Supply Chain Management | Conf. | Open CRs & CRs closed in month. | Conf. | Weekly | Count |
| **3.2.1** | Purchasing Volume | Purchasing | Conf. | Total purchasing volume and per FTE. | Conf. | Weekly | € / FTE / month |
| **3.2.2** | Supplier On-Time Delivery Rate | Purchasing | Conf. | Percentage of PO line items delivered on time. | Conf. | Monthly | % |
| **3.2.3** | Material Cost Variance (CoBOM YoY) | Purchasing | Conf. | YoY change in costed BoM per product. | Conf. | Monthly | % (YoY change) |
| **3.2.4** | Material Availability | Purchasing | Conf. | Share of material arrived on time for production start. | Conf. | Monthly | % |
| **3.3.1** | Order-to-Delivery Time | Fulfillment | Conf. | Lead time from order to delivery. | Conf. | Quarterly | Days |
| **3.3.2** | Lead Time Bottleneck Impact | Fulfillment | Conf. | Avg. delay from bottlenecks. | Conf. | Daily | Days |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **3.3.3** | On-Time Delivery Rate (Customer) | Fulfillment | Conf. | Deliveries arriving on time. | Conf. | Weekly | % |
| **3.3.4** | On-Time Delivery Rate (Intercompany) | Fulfillment | Conf. | Delivery line items arriving on time. | Conf. | Monthly | % |
| **3.3.5** | Shipping Cost Ratio | Fulfillment | Conf. | Shipping cost per order vs order value. | Conf. | Quarterly | % |
| **3.4.1** | Inventory Turnover | Warehouse | Conf. | How many times inventory cycles per year. | Conf. | Monthly | turns / year |
| **3.4.2** | Daily Warehouse Transactions | Warehouse | Conf. | Inbound, movements, outbound per day. | Conf. | Yearly | Tx/day |
| **3.4.3** | Completed Shipments | Warehouse | Conf. | Completed item fulfillments. | Conf. | Daily | Count |
| **3.4.4** | Warehouse Space Utilization | Warehouse | Conf. | Share of used storage volume. | Conf. | Daily | % |
| **3.5.1** | Processing Time Quality Check | Quality Control | Conf. | Time from start to end of final inspection. | Conf. | Monthly | X |
| **3.5.2** | Inbound Defect Rate | Quality Control | Conf. | Percentage of inbound deliveries with defects. | Conf. | Monthly | % |
| **3.5.3** | Outbound First Pass Yield | Quality Control | Conf. | % of systems failing outbound inspection. | Conf. | Monthly | % |
| **3.5.4** | Complaint Rate | Quality Control | Conf. | % of deliveries ending up with a customer complaint | Conf. | Monthly | % |

Note. Conf. is a placeholder for confidential values, which must not be displayed. *Trinity = Quantum Systems' dual-use drone, Vector = Quantum Systems' defense drone for reconnaissance

## V. Data Integration Specification - Jira Repair Ticketing

The following "Data Integration Specification" was shared with the internal data scientist to implement the Jira repair ticketing data model. Other requests were prepared in a similar manner.

**Purpose and Scope:** I want to evaluate how long each ticket was in each status (Open, Request Repair, Remote Repair, Repair Evaluation, Pending Customer Approval, Repair in Progress, Ready to Fly, Log Evaluation, Ready to Pick). In the future I also want to evaluate the original estimate (How long the employee estimated the repair would take) and time tracking (how many hours actually needed by the employee), together with the costs (hourly rate eur, material costs eur, total costs eur).

**Two Tables are required:** a) repair_ticketing_historical_data – event-level log of all status changes and key activities. B) repair_ticketing_current_data – fact table → current snapshot of each ticket with calculated durations per status

1. **Table a) - repair_ticketing_historical_data**

| Column Name | Description | Example |
|---|---|---|
| **ticket_id** | Unique Jira issue key or ID | REPAIR-102 |
| **activity_type** | Type of logged event (e.g., status_change, creation, assignment_change) | statuscategorychangedate |
| **changed_by** | User who performed the action | XX |
| **changed_at** | Timestamp of the change (including minutes) | 2025-05-30T17:15:00 |
| **from_...** | Original value (if applicable) | Repair in Progress |
| **to_...** | New value (if applicable) | Ready to Fly |

**Table b) – repair_ticketing_current_data:** Represents the current state of each repair ticket along with calculated status durations and additional ticket attributes. This is the main table used for Power BI dashboards and KPI evaluation.

| Column Name | Description |
|---|---|
| **ticket_id** | Unique Jira issue ID |
| **created_at** | Ticket creation date |
| **ticket_name** | Ticket summary or title |
| **current_status** | Current Jira status |
| **status_request_repair_entered_at** | Timestamp when ticket entered "Request Repair" |
| **status_request_repair_duration_sec** | **Total time (in seconds)** spent in "Request Repair" (aggregated from historical data) |
| **status_repair_evaluation_entered_at** | Timestamp when ticket entered "Repair Evaluation" |
| **status_repair_evaluation_duration_sec** | Total time in this status |
| **status_pending_customer_approval_entered_at** | Timestamp when entered this status |
| **status_pending_customer_approval_duration_sec** | Total time in this status |
| **status_repair_in_progress_entered_at** | Timestamp when entered this status |
| **status_repair_in_progress_duration_sec** | Total time in this status |
| **status_ready_to_fly_entered_at** | Timestamp when entered this status |

| | |
|---|---|
| **status_ready_to_fly_duration_sec** | Total time in this status |
| **status_log_evaluation_entered_at** | Timestamp when entered this status |
| **status_log_evaluation_duration_sec** | Total time in this status |
| **status_ready_to_ship_entered_at** | Timestamp when entered this status |
| **status_ready_to_ship_duration_sec** | Total time in this status |
| **status_done_date** | Date when ticket reached final "Done" or "Ready to Ship" state |
| **paid_by** | Jira custom field – value taken directly from ticket |
| **time_tracking_sec** | Jira time tracking (in seconds) |
| **original_estimate_sec** | Original estimated time (in seconds) |
| **service_type** | Jira field (Type of Service) |
| **priority** | Jira field (Priority) |
| **platform** | Jira field (e.g., Vector, Trinity, etc.) |
| **hourly_rate_eur** | Jira custom field (future use) |
| **material_cost_eur** | Jira custom field (future use) |
| **total_cost_eur** | Jira field – taken directly from ticket (no recalculation) |

## VI. Operations1 Data Export Pipeline

In Operations1, production processes are centered around documents and reports. A document represents a work instruction that specifies how a particular process step should be executed. Each time a document is created or revised, it receives a new document ID, while a stable document base ID groups all revisions of the same underlying instruction. A report is the executed instance of such a document: whenever an operator completes a process step, a report is created based on the corresponding document and this execution. Reports therefore form the core fact data for production analytics and are used to derive cycle times, production output, Maiden First Pass Yield, and other Operations1-based KPIs. Additional entities provide the context for these executions. Classes define generic process types and hold characteristics such as product type or revision, which are later used for filtering and aggregation. Orders bundle multiple reports for a drone or batch and enable analysis at an order level rather than only per individual process step. Users represent operators and are linked via their e-mail addresses to HR data (e.g. in Personio) to derive attributes such as production location.

Table 7 - Overview of Operations1 export scripts, API resources and JSON outputs

| Script | Main API resource(s) | JSON outputs | Description |
|---|---|---|---|
| **fetch_classes.py** | Classes | classes.json, class_characteristics.json | Exports all Operations1 classes and their characteristics (e.g. product type, revision). These attributes are later used as dimensions for filtering and aggregating production KPIs (e.g. by platform or revision). |
| **fetch_documents.py** | Documents | documents.json, document_x_characteristic.json | Exports all work-instruction documents and their characteristics. Document base IDs are used to group different document revisions and to calculate metrics such as average cycle time across the same underlying instruction. |
| **fetch_users.py** | Users | users.json | Exports active and archived Operations1 users. User e-mail addresses are matched to Personio to infer attributes such as production location for reports and orders. |
| **fetch_orders.py** | Orders | orders.json, report_x_assigned_location.json | Exports orders that bundle multiple reports for a drone or batch, as well as the assigned groups/locations. This enables KPIs and views at the order or site level rather than only per individual report. |
| **fetch_reports.py** | Reports | reports_raw.json, report_x_characteristic.json | Exports executed process steps (reports) with timestamps and characteristics. Reports are the core fact data for production analytics, providing cycle times and user inputs needed for KPIs such as production output and Maiden First Pass Yield. |
| **core_reports_data.py** | — (derived) | core_reports_data.json | Combines reports_raw and documents into a cleaned, analytics-ready reports fact table with per-report cycle-time metrics and join keys for Power BI; this dataset is the base for all Operations1-based production KPIs. |

Figure 6 below shows how the Python scripts call the Operations1 REST API endpoints (reports, orders, classes, documents, users), write the respective JSON files, and finally combine reports_raw.json and documents.json in core_reports_data.py into the analytics-ready core_reports_data.json fact table used for production KPIs.

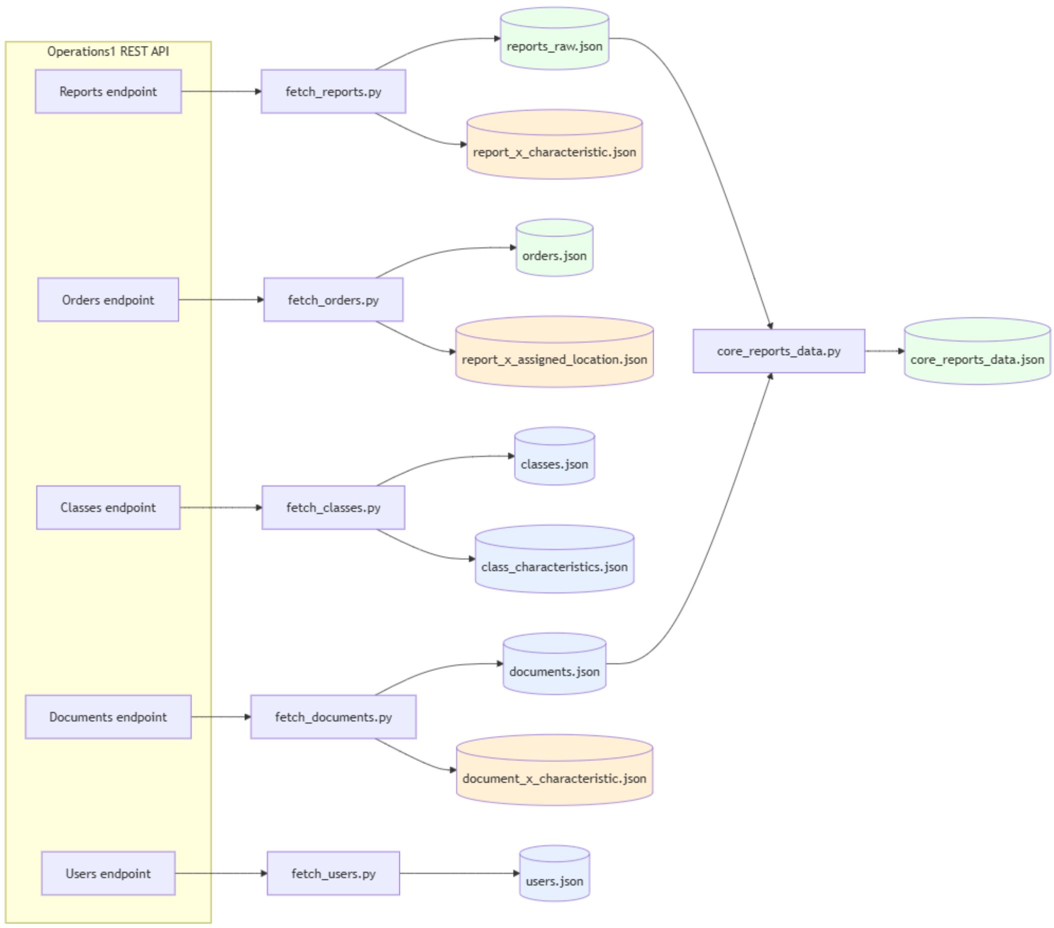


Figure 6 - Operations1 data export pipeline: Python scripts calling REST API endpoints

## VII. KPI-level decision justifications for exclusion

Table 8 - Detailed screening decisions for KPIs removed from the initial longlist, including primary exclusion criterion and rationale.

| KPI | Primary Screening Criterion |
|---|---|
| **Revenue per Operations Hour** | Strategic Relevance & Actionability: No actionable insights for Operations. |
| **Home Office Rate** | Strategic Relevance: Affects only few Ops employees; weak link to operational performance. |
| **Revenue per Production Hour** | Strategic Relevance & Actionability: Does not support concrete operational decisions. |
| **Cycle Time (Production steps)** | **Data Readiness & Execution Costs:** Cycle-time data dominated by outliers and unreliable timestamps (median 3.8 h vs. expected ≈1 h; >50% implausible values); additional Operations1 API functionality required but currently unavailable. |
| **Schedule Adherence** | Data Readiness & Execution Costs: No standardized planning; poorly maintained work orders; frequent ad-hoc changes reduce KPI reliability. |
| **Work Orders per Production Planner** | Strategic Relevance & Actionability: High variance in order size/effort; limited interpretability. |

| | |
|---|---|
| **Rework Rate & Top 5 Rework Topics** | Data Readiness & Execution Costs: Migration to Jira still ongoing; unstable setup and insufficient historical data. |
| **Labor Utilization Rate (OEE)** | Data Readiness & Execution Costs: Operations1 does not provide process-level time tracking. |
| **Internal vs External Workload Distribution** | Data Readiness & Execution Costs: R&M process newly migrated to Jira; required fields only recently introduced. |
| **Blocked Inventory Ratio** | Data Readiness: Blocking information insufficiently tracked. |
| **Open & Closed Change Requests** | Strategic Relevance & Actionability: Low leadership value; limited actionable insight. |
| **Purchasing Volume** | Strategic Relevance: Already tracked by Supply Chain; limited relevance for Ops leadership view. |
| **Material Cost Variance (CoBOM YoY)** | Data Readiness & Execution Costs: Requires cost-BOM and financial data not yet integrated; high modelling effort. |
| **Order-to-Delivery Time** | Strategic Relevance & Actionability: Mostly relevant only for Trinity drone; limited applicability across platforms, as fulfillment dates differ. |
| **Lead Time Bottleneck Impact** | Execution Costs: Attractive metric but requires complex modelling beyond thesis scope. |
| **Inventory Turnover** | Data Readiness & Execution Costs: Warehouse move and RF Smart rollout lead to unstable baseline; implementation out of scope. |
| **Daily Warehouse Transactions** | Data Readiness & Execution Costs: Strong task-dependent variation; would require extensive categorisation; limited actionability. |
| **Warehouse Space Utilization** | Data Readiness & Execution Costs: Warehouse relocation and RF Smart introduction prevent stable measurement. |
| **Processing Time Quality Check** | Data Readiness & Execution Costs: Same timestamp and data-quality limitations as production cycle time. |
| **Complaint Rate** | Data Readiness & Execution Costs: Is currently watched by Support team but not tracked automatically and therefore too expensive to execute for now. |
| **Material Availability** | Data Readiness & Execution Costs: Data Quality is not given in NetSuite, can’t be calculated accurately |
| **Internal Audits Completed vs Planned** | Strategic Relevance & Actionability: Relevant for local quality- and compliance management, but limited added value at Operations leadership level; |
| **Audit NCRs (Minor / Major),** | Strategic Relevance & Actionability: Important for detailed quality management, but too granular for the leadership view |

## VIII. Data-Quality Assessment for Operations1 Cycle-Time KPI

To assess the feasibility of cycle-time KPIs in Operations1, exploratory analysis was conducted for the Main Fuselage assembly process (10,045 reports between 01.01.2025 and 05.10.2025). The distribution (Figures 7-8 below) shows extreme dispersion: a median of 3.79 hours despite an expected duration of ≈1 hour per step, a mean of 275 hours, a standard deviation of 581 hours, and 46.6% of reports with cycle times ≥8 hours. The combination of very short and very long durations suggests that timestamps mix actual work with waiting and administrative time, driven by inconsistent logging and the absence of usable pause information in the Operations1

API. Consequently, cycle-time-based KPIs were classified as failing the Data Readiness & Execution Costs criterion and were moved to the KPI backlog.

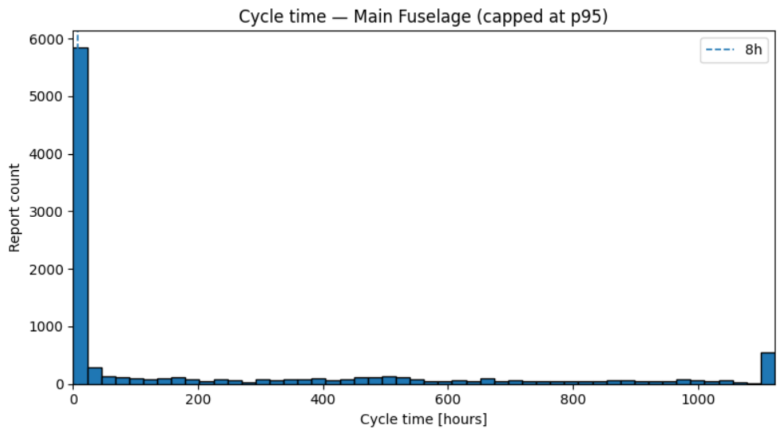


Figure 7 - Histogram based on Operations1 data for Main Fuselage assembly processes

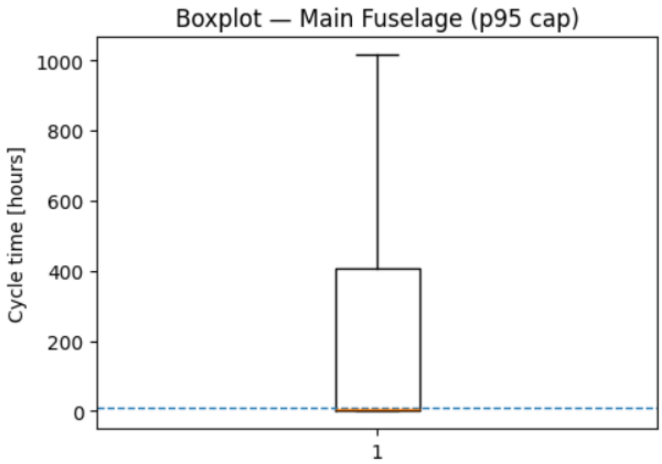


Figure 8 – Boxplot based on Operations1 data for Main Fuselage assembly reprocess

## IX. Excerpt Power BI – Leadership Dashboard

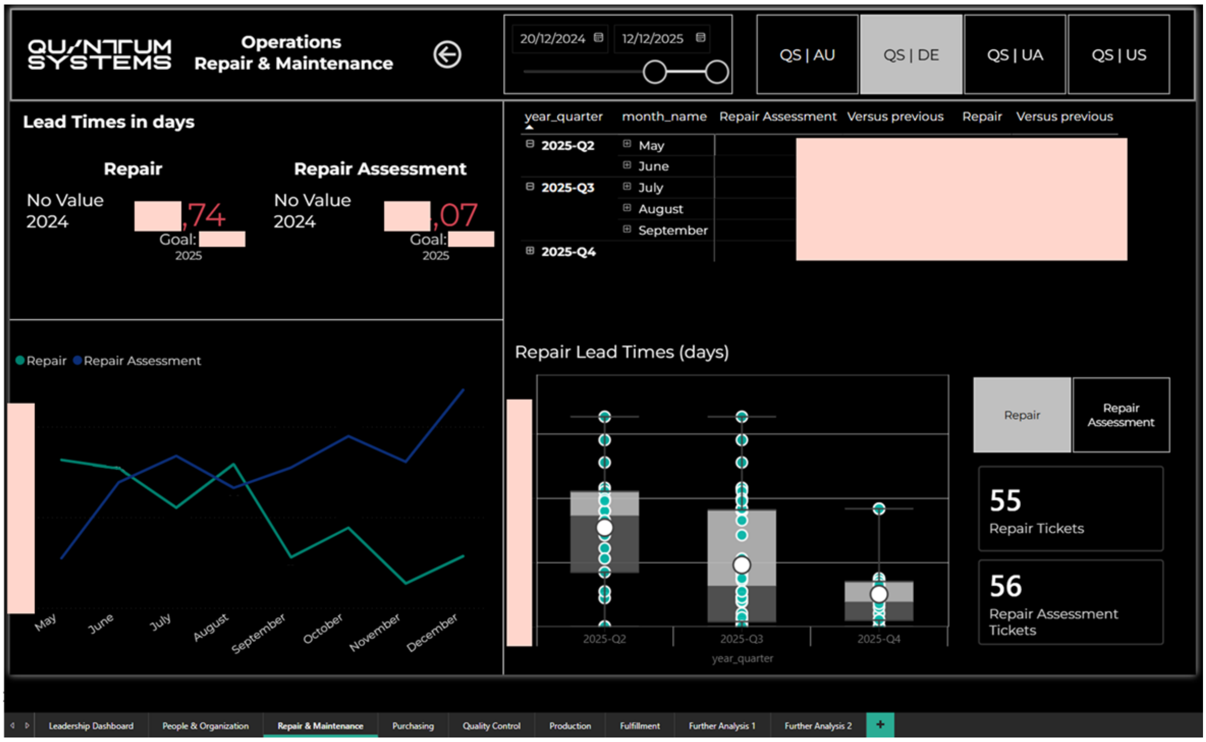


Figure 9 - Repair & Maintenance deep-dive dashboard in Power BI (all values anonymized).

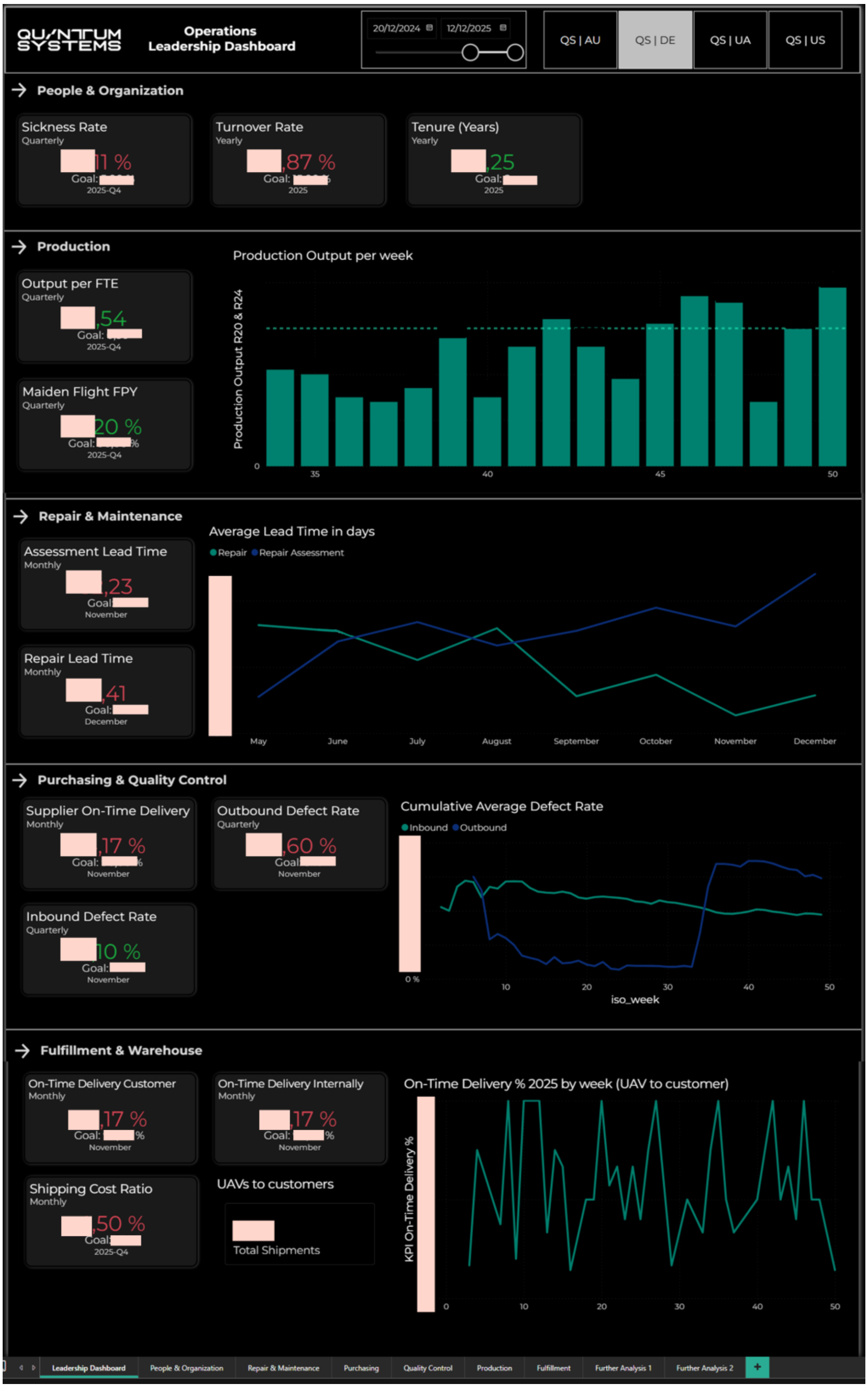


*Figure 10 – Full Operations leadership dashboard in Power BI (People & Organization, Production, Repair & Maintenance, Purchasing & Quality Control, and Fulfillment & Warehouse; all values anonymized).*

## X. Table 9 Summary of evaluation results

| Pillar | Indicator | Situation before artifact | Situation after artifact (end of project) |
|---|---|---|---|
| **Volume** | Leadership KPIs consolidated in a single view | No integrated leadership dashboard; mix of source-system screens and ad-hoc Excel reports; some KPIs not tracked consistently or compiled manually. | 14 leadership-relevant KPIs consolidated in one Power BI dashboard with a common structure and navigation. |
| **Accessibility** | Systems and reports required for leadership KPI preparation | KPIs and operational figures prepared from approx. five systems (e.g. NetSuite, Personio, Jira, Operations1, Excel files) and around ten separate reports; some information only available via a physical shopfloor board. | Live Power BI leadership dashboard as primary entry point; several separate reports, ad hoc analysis and the physical shopfloor board no longer required for the KPIs included in the dashboard. |
| **Quality** | Implemented KPIs with sufficient data quality for trend analysis | KPI data partially inconsistent, manually maintained and with limited historical coverage for several measures. | 10 of 14 final KPIs with sufficient data quality for both historical and current analysis; 4 KPIs expected to be reliable going forward but with limited history. |
| **Governance** | Awareness of KPI ownership | KPI owners, calculation logic and reporting intervals not centrally documented; responsibilities not transparent across teams. | KPI framework assigns an owner to each KPI and documents definitions and intervals; interviews indicate that 9 of 11 KPI owners are aware of their responsibility and of the documentation. |