EHS Data Integration into Production Monitoring Tools

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Abstract: With the rapid advancement of digitalization, data modeling and management have become increasingly significant. This study explores the digitization of diverse data types and their interconnection within a real-world automotive manufacturing environment. The proposed framework integrates two independent online applications; one responsible for collecting and processing production data and the other designed to assess ergonomic conditions at workstations. The study examines the feasibility of linking these systems, enabling continuous monitoring of operator workload. This integration aims to mitigate occupational health risks and evaluate how ergonomic inefficiencies at workstations can influence product quality. The findings highlight the potential for proactive intervention in production processes by leveraging digital tools to enhance workplace ergonomics and manufacturing efficiency.

Keywords: data digitization; production data; digitization, workstation ergonomics, ergonomics evaluation.

1. Introduction

Digitization is a trend that is reshaping companies and businesses in the immediate and long term [1]. Its impact is already significant and will continue to be significant; several authors associate it with the industrial revolution [2-4]. Digitization contributes to increasing productivity and profitability in companies by enabling innovative changes and improvements in products, processes and business models. In this regard, the availability and handling of data in industrial companies has improved, which is still the goal of further improvement.

Batini, C. and Scannapieca, M. [5] understand data as real-world objects in a format that can be stored, retrieved and processed by software procedures and communicated over a network. According to the Data Management Association (DAMA), data is a representation of facts such as text, numbers, graphics, images, sound or video. It is important to understand the difference and relationship between data and information. Information is data that has been placed in a context that includes data elements, time, format and relevance to the given use of the data [6].

At the same time, it is necessary to work with quality data. Olson, J. [7] defined data quality as the quality that meets the requirements for its intended use or depends on the intended use of the data itself. The data used must be accurate, timely, appropriate, complete, understandable and trustworthy to satisfy the intended use. Cichy, C. and Rass, S. [8] consider accuracy, completeness, timeliness and consistency to be the main characteristics of data quality. Ramasamy, A. and Chowdhury, S. [9] added a fifth characteristic to these characteristics, which is correctness.

Digitization affects the work with data. Their processing process can take place in the steps of data collection, transmission, processing, provision and use. Data is available through digital networks, which allows automated data analysis and the use of results for management processes based on predefined rules and cyberphysical systems. Thus, there are many challenges associated with the effective management of different types of data. In addition to dealing with the significant volume of big data and the abovementioned facts, effective data management, together with data archiving for future use, has an irreplaceable place [10-11].

Data is also the basis for artificial intelligence and the use of its potential for various purposes. Digitalization and artificial intelligence lead to changes in work design, work procedures and organizational structure. They therefore also have an impact on occupational safety and health [12].

This article presents the integration of two independent online applications. The first online application is focused on the collection and processing of production data and the second on the assessment of ergonomic conditions at workstations. The aim of this integration is to mitigate occupational health risks and evaluate how ergonomic inefficiencies at workstations can affect product quality.

2. Methods and Materials

The case study described in these pages focuses on integrating multiple data sources from production analytical tools, emphasizing Environmental, Health, and Safety (EHS) assessments and their connection with other production indicators.

The study specifically examines how to ingest data from HumanTech software into the Palantir Foundry platform, particularly the Cycle Time Deviation (CTD) application. The primary goal is to transfer ergonomics EHS scores from assessments and generate production reports detailing which operator, at which station, with which EHS score, spent how many minutes, and to understand the impact on assembly times. These statistics aim to monitor the duration of working times at the most problematic stations to support the prevention of occupational diseases and to evaluate the impact of an unbalanced process on manual workers' effectiveness.

The methodological approach of this research is structured in two main stages. The first stage focuses on understanding current state procedures and analysing how the process operates. Building

on this understanding and identifying the problem, the second stage proposes a solution.

Given the large volume of data processed by the solution, ensuring data quality is critical. To manage this, the Palantir Foundry platform is utilized, with the Pipeline Builder module employed to filter and clean data formats, ensuring accurate calculations. In the logical layer, numerous operations and processes work in the background to prepare high-quality data and maintain proper formatting.

This study is being developed for a major automotive company with a focus on assembly processes.

The integration project was based on data collected from over 30 Just-In-Time (JIT) manufacturing plants in the Europe and Africa and more than 50 JIT plants across North and South America, all part of a major global automotive manufacturer. The scope of the data included several million records over a continuous six-month period, encompassing production performance metrics from the CTD system and ergonomic assessments from HumanTech.

To evaluate the success of the integration, the study applied two main criteria: (1) the accuracy of data linkage between HumanTech and CTD systems, and (2) the coverage rate, i.e., the percentage of stations successfully enriched with ergonomic scores in the CTD front end. Additional technical KPIs included the frequency and reliability of data synchronization, average pipeline latency, and error logging rates.

The core data transformation pipeline involved the following steps:

- Ingestion of HumanTech data from Snowflake and CTD data from MES and offline sources.
- Application of regular expressions (RegEx) via the Palantir Pipeline Builder to decompose complex hierarchical fields (such as "OU_PATH") into structured dimensions (Plant, Line, Station, etc.).
- Filtering and normalization of data columns to ensure uniform formatting across sources.
- Mapping of ergonomics scores to specific stations and shifts using unique identifiers.
- Validation of output through historical backtesting and feedback from line supervisors.

This structured approach ensured that integrated datasets were accurate, timely, and compatible with existing production analytics, providing a scalable basis for future digital health and safety monitoring.

2.1 Case study description

Currently, there are two distinct systems in place for managing production and ergonomic data. The first system, known as the Cycle Time Deviation (CTD) application, operates on the Palantir Foundry platform. It gathers and processes production data from the corporate Manufacturing Execution System (MES) and other offline sources, presenting this information through a user-friendly interface. This interface is split into two sections. The first section, the CTD Workshop application, is utilized for real-time production monitoring. It showcases key indicators and color-coded management data, offering line leaders a clear and concise view of their process health. The second section, the Shift Report application, is used for reporting, either at the end of work shifts or as needed and includes essential indicators specific to various plants (refer to Fig.1).

The second system, called HumanTech, is designed for ergonomic analysis. These assessments can be performed in two ways. The first method involves recording a video and analysing it with the HumanTech front-end application, where an AI tool evaluates body movements and provides a detailed assessment. The second method involves manually entering tasks into the system for evaluation. These analyses generate a difficulty score for each task related to the assembly process at specific workstations, helping to determine the complexity of assembly operations and the overall process difficulty (see Figure 2).

Currently, fixed rules are used for rotating

operators between stations without considering ergonomic risk assessments. Due to the large scale of production lines, it is challenging to track which operator worked at which station and the ergonomic difficulty score assigned to each station.

An automated solution is being sought to address these challenges. The proposed system would enable tracking and reporting of EHS scores for each station, as well as identifying operators who have skipped rotations or spent excessive time at specific stations. Additionally, the system would include active reporting and push notifications for line leaders, ensuring timely alerts to mitigate occupational diseases and improve compliance with ergonomic standards. This approach aims to enhance operator rotation monitoring and promote workplace health and safety.

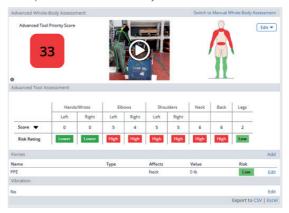


Figure 2: Snapshot from HumanTech software with ergonomics study made on assembly station.

Inspect Cycle Inspect Scanner Inspect Scanner										⊙ JPH	Defects			
Station	Cycle Punctuality % (last hour)	Cycle Punctuality % (current shift)	Over Target Count (last hour)	Over Target Count (current shift)	Over Target Time (last hour) secs	Over Target Time (current shift) secs	Scanners RFT % (last hour)	Scanners RFT % (current shift)	Fasteners RFT % (last hour)	Fasteners RFT % (current shift)	Station	This hour JPH	Total Shift Jobs	
FSA 01 - A	72%	72.3%	26	28	245	879	100%	100%	No value	No value	PREKLADACI ROBOT	42	51	
FSA 03 - A	92%	92.5%	8	8	135	135	100%	100%	No value	No value	E-TEST-D RH	11	13	
FSA 07 - A LH	21%	31,4%	34	35	341	409	95%	96.1%	No value	No value	E-1ES1-D KH	**	13	
FSA 07 - B RH	42%	49%	25	26	172	228	100%	100%	No value	No value	E-TEST-D LH	11	13	
FSA 09 - A LH	84%	87%	7	7	8	8	No value	No value	No value	No value	E-TEST-C RH	16	19	
FSA 09 - B RH	84%	87%	7	7	8	8	No value	No volue	No value	No value	E-TEST-C LH	16	20	
FSA 10 - A LH	91%	92.5%	4	4	6	6	100%	98%	No value	No value	E-IESI-C LH	16	20	
FSA 10 - B RH	91%	92.5%	4	4	25	25	100%	98%	No value	No value	E-TEST-B RH	11	13	
FSA 14 - A LH	40%	48.1%	27	28	328	329	88%	90.4%	No value	No value	E TECT BILL	11	12	
FSA 14 - B RH	42%	50%	26	27	303	304	95%	94.1%	No value	No value				
FSA 15 - A LH	73%	74.1%	12	14	13	16	No value	No value	No value	No value	▲ Alerts			
FSA 15 - B RH	73%	74.1%	12	14	13	16	No value	No volue	No value	No value	Station	Metric Name	Value	42
FSA 16 - A LH	77%	81.1%	10	10	100	100	No value	No value	No value	No value				+=
FSA 16 - B RH	80%	83%	9	9	99	99	No value	No value	No value	No value	FSA 07 - A LH	Cycle Punctuality % (last hour)	20.9%	
FSA 18 - A - Robot Backup LH	93%	92.3%	3	4	7	9	No value	No value	100%	100%	FSA 07 - A LH	Cycle Punctuality % (current shift)	31.4%	
FSA 18 - B - Robot Backup RH	93%	90.4%	3	5	37	76	No value	100%	100%	66.7%	FF1.14	Cycle Punctuality %	40%	
FSA 18 - A - Robot LH	100%	98.1%	0	1	0	15	No value	No value	99%	98.8%	FSA 14 - A LH	(last hour)	40%	
FSA 18 - B - Robot RH	100%	98.1%	0	1	0	15	No value	No volue	100%	99.2%	FSA 07 - B RH	Cycle Punctuality % (last hour)	41.9%	
FSA 19 - A LH	81%	83.9%	9	9	182	182	No value	No value	98%	98.2%	FSA 14 - B RH	Cycle Punctuality % (last hour)	42.2%	
FSA 19 - B RH	92%	92.9%	4	4	40	40	No value	No volue	100%	98.2%	FSA 14 - A LH	Cycle Punctuality %	48.1%	
FSA 20 - A LH	89%	89.3%	5	6	5	6	No value	No value	No value	No value		(current shift) Cycle Punctuality %	48.1%	

Figure 1: Snapshot from CTD Workshop application with general overview.

One of the side benefits of this application will be the monitoring of ergonomics scores and their impact on cycle time duration (assembly times), as well as the potential to evaluate their impact on the final product quality and scrap rate.

2.2 Case study solution process

The case study aims to integrate two separate systems: the HumanTech application, which assesses ergonomic studies, and the CTD application, which processes and visualizes production data. Since these systems run on different platforms with unique data structures, the integration will involve expanding the existing CTD application with new modules and analyses. The first step is to extract and upload HumanTech data into the Palantir Foundry environment to review its format and structure. During this process, relevant datasets for integration will be identified and filtered to match the CTD application's current format. The objective of this integration is to display ergonomic EHS data alongside station visualizations within the CTD Workshop and Shift Report front-end applications (see Figure 3).

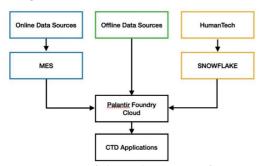


Figure 3: Diagram of the implementation of ergonomics studies into the CTD application.

This study examines the feasibility of integrating these two systems, the adjustments required to map their data effectively, and the development of a unified data structure for processing within the CTD application.

3. Results and Discussion

During the case study, it was discovered that HumanTech data is stored in Snowflake databases and systematically organized into numerous partial datasets. Since these are external datasets, their integration into Foundry will require setting up periodic updates to ensure automatic data synchronization.

For the study, a dataset named "PUBLIC"."CACHE_ JOB_ASSESSMENT_VIEW" was selected. From this dataset, only a limited number of columns will be retained. A key column, "OU_PATH", contains hierarchical information such as:

- Continent
- Division
- Plant name
- Line name
- Process categorization (e.g. logistics, production, maintenance) in certain cases.

Since this information is stored in a single row without the desired structure, the data needs to be cleaned and restructured using the Pipeline Builder tool in Palantir Foundry platform (see Figure 4).

Data cleaning will involve utilizing a series of synchronized datasets and applying Regular Expressions (RegEx) to split the information into multiple columns. To ensure compatibility between data sources, standard naming conventions must be used. For example, GB-COV represents GB (Great Britain), and COV stands for Coventry (see Figure 5).

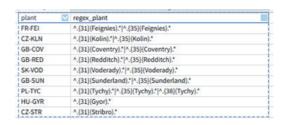


Figure 5: Example of regular expressions.

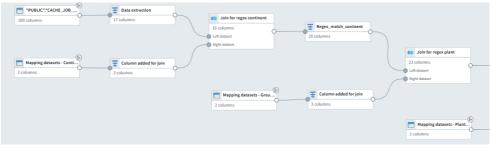


Figure 4: Pipeline Builder – Data processing tool in the Foundry platform.

These newly created columns will serve as mapping fields to join Snowflake data with the Foundry CTD application.

The ergonomic EHS scores are stored in two columns within the dataset:

- 1. MSDAI_SCORE Represents the baseline analysis.
- 2. MSDAI_SCORE_FOLLOWUP Represents the reassessment score after modifications at a station.

By default, the MSDAI_SCORE is used unless a follow-up assessment (MSDAI_SCORE_FOLLOWUP) has been conducted. If the follow-up score is lower, it indicates successful optimization, and this score is retained in the system as the improvement score. In such cases, the MSDAI SCORE FOLLOWUP should be prioritized over the MSDAI_SCORE for future analyses.

Integrating these datasets with the ergonomic scoring system will create a seamless connection between HumanTech and CTD, enhancing reporting and process optimization.

The study's results highlight the transformative potential of digital data integration in manufacturing. The automated analytical approach improves datadriven decision-making, enabling a more accurate assessment of ergonomic risks. Our findings are consistent with previous research that emphasizes challenges in data quality and integration, highlighting the importance of data filtering and preprocessing for reliable analytical outcomes. By establishing an automated link between production and ergonomic assessment tools, this study contributes to a broader understanding of how digitization can enhance industrial health and safety standards. Future research should explore standardized methodologies for evaluating the degree of digitalization in industrial enterprises, ensuring that digital transformation aligns with both efficiency and worker well-being.

Although the project is still in its early deployment phase, preliminary findings have already uncovered key challenges and opportunities for standardization. A global data quality audit revealed that more than 80% of JIT plants worldwide had incomplete or improperly filled ergonomic assessments. In roughly 50% of cases, assessment data were either missing entirely or only partially captured – often covering just fragments of the assembly process rather than the full operational cycle. These gaps severely limited the utility of the data for ergonomic risk evaluation and process optimization.

The integration of ergonomic scoring with cycle time analytics exposed inefficiencies in existing operator rotation practices. Specifically, stations with high ergonomic risk scores were not being staffed with sufficient frequency of operator changeovers. This misalignment increased the long-term risk of operator fatigue and injury. As a result, several European plants have already begun implementing new rules for employee rotation and monitoring based on live EHS scores – to better manage workload distribution and improve compliance with ergonomic standards.

These early insights highlight the potential of the system to act not only as a data integration platform but also as a driver for global process standardization and health-and-safety policy reform across diverse manufacturing sites.

4. Conclusions

This study demonstrates the advantages of integrating ergonomic assessment tools with production monitoring systems, showcasing the potential of cloud-based platforms like Palantir Foundry in managing large-scale industrial data. By merging these datasets, manufacturers can proactively address ergonomic risks, optimize operator workload distribution, and enhance overall production quality. The research lays the groundwork for further studies on digitalization metrics in manufacturing, contributing to the ongoing evolution of smart industry practices.

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