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RESEARCH PAPER

Industry 5.0 and Data Science: implementation of data capture from a human-centered perspective in a metal-mechanic company

Israela Peixer Lorenzini[1], Cristina Keiko Yamaguchi[1], Merisandra Côrtes de Mattos[1]

[1]Universidade do Planalto Catarinense (UNIPLAC), Lages, SC, Brazil.

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ABSTRACT

Objective: To analyze the implementation of data capture in a medium-sized metal-mechanic industry, considering factors related to Digital Transformation (DT) under the human-centered approach of Industry 5.0 (I5.0).

Methodology: Quali-quantitative study developed through action research in five phases (Oct/2023 – Jul/2024), and a survey with its instrument based on the UTAUT and MD3M models.

Findings: Six forms were identified, containing 108 fields involving 51 unique attributes, with high redundancy in the entry of general descriptions. The digital data collection, integrated with the company's ERP system, concluded with 10 forms and 35 unique variables, reducing redundant fields by 72%. Employees were involved throughout the process, with the most interaction occurring during training sessions and analysis meetings. The survey results show over 87% acceptance across the four main constructs of the UTAUT model, and the correlations between variables and participation levels indicate a reduction in users' insecurities regarding the adoption of new technology, reinforcing that the human-centered approach was essential for the acceptance of the new data collection format.

Research limitations: Technology implementation time, absence of Industry 5.0 maturity models and inability to measure data-management maturity using the MD3M model.

Practical implications: Identification of challenges in IT-operations coordination; highlighting the need for an empathetic and collaborative approach in DT, as revealed by the reduction of resistance through employee participation in the process.

Originality: Practical demonstration that the challenges of DT can be overcome through the active participation of employees, highlighting — through the correlations found — the impact of a human-centered approach on technology implementation.

Keyword: Data-driven organization; Data capture; Industry 5.0; Human-centered approach.

INTRODUCTION

Industries play a significant role in the economy, accounting for 21.3% of the global gross domestic product in 2023 and 25.5% in Brazil as of May 2024 (CNI, 2024; UNIDO, 2024). To remain competitive in the market, organizations need to differentiate by applying various strategies to expand their advantages and maximize their profits, making the development and practical application of an action plan necessary (Hasegawa et al., 2025). With globalization, meeting customer demands has become essential, making quality control (QC) a key factor in preventing defects, reducing waste, and ensuring customer satisfaction. QC must be well-structured and followed throughout all stages of production (Tiensuu et al., 2021).

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Since the First Industrial Revolution, technological advancements have been transforming industry, with increasingly faster and more complex cycles (Demir et al., 2019). Industry 4.0 (I4.0) has its potential rooted in the ability to integrate digital and physical systems, optimizing efficiency and improving organizational performance through real-time data exchange, significantly transforming their operations and competitiveness (Khan and Emon, 2025). In this context, digital transformation (DT) introduces information and communication technologies (ICTs) into production processes, digitizing data and promoting greater integration between systems, people, and machines (Colombari et al., 2023; Cruzara et al., 2020; Zizic et al., 2022).

With DT, the large volume and complexity of data present challenges to QC, leading to an overload for professionals, which can delay responses and hinder the detection of failures (Tiensuu et al., 2021). Technological innovations have reshaped the strategic domains of organizations, requiring the intelligent use of data as a true source of value (Rogers, 2017). Data science (DS) emerges as a response, offering interdisciplinary approaches to generate value from data, addressing everything from capture to dissemination (Han and Trimi, 2022; Moraes, 2023). This demands the reskilling of the workforce, with new competencies focused on technology and data handling (Kolade and Owoseni, 2022).

In I4.0, the adoption of technologies transforms industrial models into a complex transition, impacting the people involved. Focused on efficiency and automation, it overlooks the resulting human costs (Nahavandi, 2019; Zizic et al., 2022). Considering the consequences of digitalization, the need for the next evolutionary step arises, aiming to address challenges such as climate change, resource crises, non-renewable energy, labor shortages, and social inequalities (Hein-Pensel et al., 2023; Pereira and Santos, 2022).

Industry 5.0 (I5.0) expands on I4.0 by placing the human at the center of DT, aiming to balance technological advancement, sustainability, and social well-being to ensure long-term resilience, focusing on human-technology interaction and its full relevance (European Commission, 2021a; Madsen and Berg, 2021; Özdemir and Hekim, 2018; Zizic et al., 2022). Although it builds upon the technologies of I4.0, I5.0 acknowledges the role that industry plays in social growth and values the development of better working conditions, aligning with the United Nations Sustainable Development Goals (UNIDO, 2022; Xu et al., 2021). Despite being innovative, its approach is still recent and requires further studies, debates, and the identification of facilitators for its effective implementation (Hein-Pensel et al., 2023; Lu et al., 2022; Zizic et al., 2022).

Based on these considerations, the objective of this research was to analyze the implementation of data capture from the perspective of the human-centered approach of I5.0 in quality control conducted in a production line of a medium-sized metal-mechanical industry in the Serra Catarinense region, focusing on the challenges and opportunities of the data domain related to DT, and seeking to identify the influences generated by this approach.

LITERATURE REVIEW

Data Domain

Although the use of data by managers is not new, with I4.0 and ICTs, its relevance has increased due to the speed and abundance of digital data, significantly impacting organizations. Data-driven companies optimize processes, innovate business models, and make more assertive decisions based on advanced analyses of large volumes of data, leveraging their embedded value potential. To generate innovation and strategic value, it is essential to treat data as an organizational asset (Colombari et al., 2023; Fischer et al., 2023; Kayabay et al., 2022; Ritter and Pedersen, 2020; Rogers, 2017).

Value creation occurs when data is integrated, contextualized, and supported by intelligent technologies and human intervention. To become a Data-Driven Organization (DDO), it is essential to restructure processes, adopt innovative strategies, and ensure efficient governance and a well-defined data science lifecycle, with the collection and use of contextualized data aligned with the company's strategy, adjusting technology, people, and management to organizational goals (Fischer et al., 2023; Kayabay et al., 2022; Pereira et al., 2019; Ritter and Pedersen, 2020; Visvizi et al., 2022). The main challenges, opportunities, and guidelines for establishing a DDO were synthesized in Table 1 and served as a reference throughout the conduct of this study.

Table 1 – Recommendations for an ODD

Author	Challenges, opportunities and guidelines
(Kayabay et al., 2022)	Understanding business prevents inconsistent outcomes
(Kayabay et al., 2022)	Overcoming the lack of domain knowledge makes it easier to identify relevant data
(Kayabay et al., 2022)	Analyzing data with objectives aligned to the organizational strategy
(De Sordi, 2019)	Integrating data modeling with process modeling, considering their properties and dimensions
(Pereira et al., 2019)	Only connected data generates relevant information
(Fischer et al., 2023)	Collecting data in a targeted way generates contextualized information
(Rogers, 2017)	Identifying essential data to understand applications and relationships
(Kayabay et al., 2022)	Prioritizing and storing data according to business activities, defining its ownership and availability
(Kayabay et al., 2022)	Aligning identified data to its possible uses
(Barbieri, 2020)	Mapping required data objects by identifying their attributes
(Kayabay et al., 2022)	Evaluating data sets to choose appropriate tools
(Kayabay et al., 2022)	Integrating technical and domain knowledge to bridge gaps between operational and analytical functions
(Rautenberg and Carmo, 2019)	Mastering the knowledge and context of the problem
(Rautenberg and Carmo, 2019)	Integrating technology and business areas to support data analysis
(Hupperz et al., 2021)	Combining tasks and processes optimizes organizational speed and capacity
(Ritter and Pedersen, 2020)	Defining data capture, transmission, and storage to extract value from data
(Hupperz et al., 2021)	Training employees to understand and democratize data
(Hupperz et al., 2021)	Developing capabilities in data management with leadership to drive change
(Hupperz et al., 2021)	Evaluating processes to improve data communication and visualization for non-technical employees
(Hupperz et al., 2021)	Defining operational leaders to apply data analysis
(Hupperz et al., 2021)	Enhancing infrastructure to process data and automate activities
(Dikhanbayeva et al., 2020)	New technologies drive the development of employee skills
(Vial, 2019)	Developing competencies and mechanisms is essential for DT and should be measured through its Digital Maturity (DM)
(Dikhanbayeva et al., 2020)	Evaluating processes from various perspectives strengthens capabilities and enables change through DT

Data Science (DS) encompasses the entire data lifecycle—from capture to dissemination—allowing knowledge to be extracted from distributed sources to support decisions, improve predictions, and optimize resources. Its use requires the integration of programming, statistics, and domain knowledge, the latter represented by the intellectual capital of the organization, which includes skills, creativity, and leadership competencies of its employees (Liebowitz and Beckman, 1998; Rautenberg and Carmo, 2019). The authors Han and Trimi (2022) propose a platform, presented in Figure 1, with four interconnected stages: Capture, Preprocessing, Mining, and Use of Results.

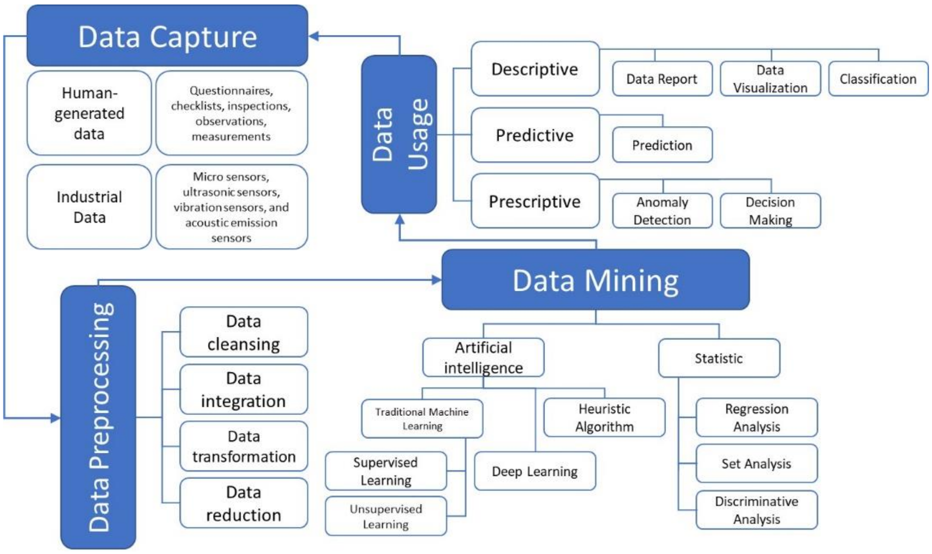

Figure 1 – CD Stages

The DS requires ethical evaluation in the use of data to avoid negative impacts, and because of this, professionals with competencies in analysis are essential for assertive decisions and the success of DDOs (Barbieri, 2020; Hupperz et al., 2021). Visvizi et al. (2022) emphasize that the combination of data collection and interpretation for knowledge extraction creates a balance between technology and human resource management.

Industry 5.0

DT, driven by Industry 4.0, integrates physical and virtual environments with ICTs, automating processes and generating data for real-time decision-making. However, its technological focus and complex implementation raise socio-environmental concerns, requiring alignment with sustainability priorities and social justice (Madsen and Berg, 2021; Saniuk et al., 2022; Xu et al., 2021; Zizic et al., 2022).

The changes brought about during transformations can create asymmetries within teams, requiring active involvement and continuous training of the workers involved. More complex tasks emerge, altering the balance between physical and mental effort with an increase in cognitive demand, requiring attention to physical, psychological, social, and cultural dimensions in technological development (Alves et al., 2023; Khamaisi et al., 2022; Kolade and Owoseni, 2022; Longo et al., 2020).

Based on its concepts, I5.0 evolves from I4.0 by proposing a sustainable and human-centered industry through the prioritization of human-machine cooperation and a focus on human needs (Madsen and Berg, 2021; Özdemir and Hekim, 2018; Pereira and Santos, 2022; Zizic et al., 2022). By combining advanced technology with human skills (creativity, complex reasoning, socio-emotional intelligence), efficiency and adaptability are enhanced, generating sustainable and resilient outcomes through dynamic responses to change. It is essential to create friendly work environments that promote well-being, learning, and empowerment for the use of new technologies (Alves et al., 2023; Cillo et al., 2022; Lu et al., 2022).

The human-centered approach of I5.0 places the human being at the core of production systems through practices focused on individual well-being and sustainable growth, which are essential for creating safe, motivating, and comfortable environments. When technologies are applied with a people-centered focus, they promote situational assistance and empathetic collaboration, strengthening the sense of purpose in daily activities. It is necessary to better understand social, cultural, physical, and psychological factors to design systems that integrate them, adapting work to human needs (Alves et al., 2023; European Commission, 2021b; Khamaisi et al., 2022; Longo et al., 2020; Lu et al., 2022).

Within this context, Lu et al. (2022) propose the Pyramid of Industrial Human Needs, presented in Figure 2. Inspired by Maslow's hierarchy, it relates the evolution of human-machine interactions to industrial paradigms through the journey of the 5 Cs: Coexistence, Cooperation, Collaboration, Compassion, and Coevolution.

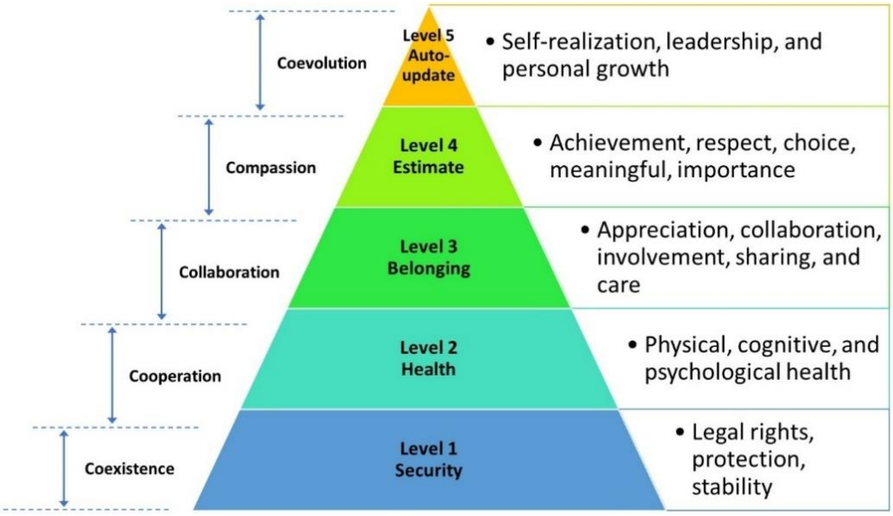

Figure 2 – Industrial human needs pyramid

As an emerging paradigm, further studies are still needed to explore the human factor in interactions with technology (Lu et al., 2022). Some research is already moving in this direction, such as Margherita and Braccini (2021), who highlight the importance of involving workers in technological implementation to balance cost reduction with well-being. However, there are challenges, such as the lack of skills to handle I4.0 technologies and limited knowledge about manufacturing processes — these were some of the difficulties encountered by the authors in their study.

For technological implementations to be truly human-centered, it is necessary to consider the complexity of interactions, considering aspects such as trust, respect, self-confidence, and self-actualization — fundamental factors for personal and professional growth, as well as for building a sustainable and integrated industrial environment. The shift in focus brought by I5.0, which values the human being, enhances the organization's intellectual capital by encouraging employee engagement in digital processes within collaborative and motivating work environments. This promotes interpersonal connections and a sense of belonging, resulting in well-being and continuous digital development (Lu et al., 2022; Madsen and Berg, 2021; Özdemir and Hekim, 2018; Zizic et al., 2022).

METHODOLOGY

This study, of an applied nature and explanatory purpose, adopts a quali-quantitative approach, combining action research and survey methods, and uses the inductive method for analysis. The research was conducted in a unit of a metal-mechanic transformation industry located in the Serra Catarinense region, which produces specific steel inputs used in the production processes of two other industrial sectors.

As shown in Figure 3, the unit has 80 employees distributed across 8 direct departments, sharing only the executive board and administrative sectors with the larger group. Production is divided into two clearly defined lines: the first for raw material (RM) transformation and the second for final processes according to customer specifications. This study focused on the Quality department and the first production line.

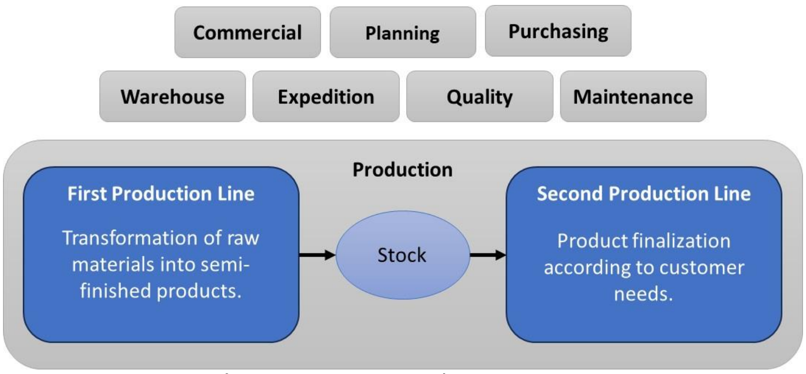

Figure 3 – Company characterization

The Quality department monitors the characteristics of the raw material (RM) and the product specifications throughout the processes, working in partnership with the Production team. It consists of three inspectors and one supervisor, all working standard business hours from Monday to Friday. The first production line transforms the RM into semi-finished products through five processes carried out on 11 semi-automatic machines. The line is managed by one supervisor and staffed by 14 employees, five working regular business hours and the others on 12-hour shifts, alternating every two days. As part of the company's strategy, three shifts with three operators run the line, with scheduled breaks on two nights in one of the shift rotations.

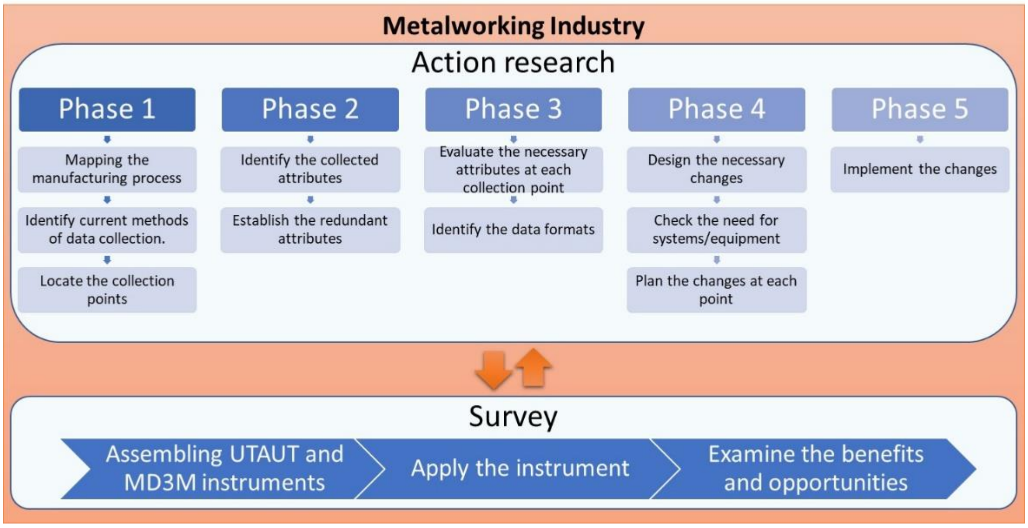

Figure 4 – Methodological design of research

The methodological procedures followed defined phases according to the chosen techniques, as shown in Figure 4. Some stages were carried out simultaneously to meet the timeline, with the study being conducted from October 2023 to July 2024. The action research allowed for mapping the necessary information for quality control and implementing data capture via digitization. The survey identified user acceptance, assessed the understanding of digital maturity, and examined the influences of the human-centered approach of I5.0.

Action research

Action research, being participatory, requires active involvement from the researcher and direct interaction with the participants (Prodanov and Freitas, 2013). Since this study addresses DS data collection implementation, it requires distinguishing between the research data and the data from the digitized production process. The analyses in this study were based on perceptions captured during the implementation, through observations and primary data collection, such as spreadsheets and checklists, which were essential for designing the first stage of DS, and did not involve digitally collected data after its completion.

The observations made were characterized as participatory and asymmetric, without a predefined instrument. Since the action research follows a qualitative approach, the collected data were analyzed for pertinence, relevance, and authenticity, being categorized and interpreted. As the data were proprietary and not authorized for disclosure, they were anonymized.

The action research was divided into 5 phases, as outlined in Table 2, guided by the guidelines for a DDO, listed in Table 1, and by the human-centered approach of I5.0. Interactions occurred both in organized groups and on a punctual and individual basis.

Table 2 – Phases for digitizing data capture

Phase	Activities	Interactions
1 Initial mapping	- Mapping of manufacturing processes - Identification of collection methods - Identification of collection points and those responsible	-Punctual meetings with specific employees
2 Identification of Attributes	- Identification of attributes in the forms - Classification of attributes - Identification of redundancy - Identification of attributes in the Product Control Plan - Correlation of identified attributes	-Theoretical training -Punctual meetings with specific employees
3 Analysis of Attributes	-Joint analysis with supervision -Preparation of employees for analysis -Joint analysis with supervision and employees -Final analysis with management	-Preparation for analysis -Targeted meetings in specific groups
4 Design and Planning	-Design with technological specifications -Planning with activity schedule and operational cycles -Budgeting for adjustments and improvements	-Involvement of IT -Involvement of technology companies -Involvement of financial management
5 Implementation of the Data Capture Stage	-Structuring digital forms -Operational cycles of data collection -Technical handover to supervision -Delivery of the final printed report version with integrated data	-Targeted meetings with specific employees -Practical training for using the technology

In Phase 2, the theoretical training covered: concepts of data, information, and knowledge; differences between analog and digital data; categorization of business data; data science with an emphasis on data capture; and DT and the changes it brings. At the end, the digitization project for quality data collection on the first production line was presented. The training conducted in Phase 3 addressed the concept of master data, the concept of entities and attributes, validation of the process diagram and checklists, as well as guidance on the joint meetings for attribute analysis.

Survey

During the first phase of the survey, a questionnaire was structured as a data collection instrument containing 45 closed-ended questions. The first section of the questionnaire aimed to characterize the target audience, their activities, and their level of participation in the implementation of data capture through attendance at training sessions and meetings.

After characterizing the target audience, it was necessary to identify critical points for the adoption of ICTs in data capture, considering multiple perspectives to strengthen capabilities and enable change through digital transformation. Based on the human-centered approach of I5.0, it is essential to analyze technological implementation with a focus on motivation, well-being, and adaptation. Hein-Pensel et al. (2023) analyzed digital maturity models from I4.0 and found that they do not place the human being at the center, although some include elements related to employee needs. Thus, the instrument was divided into two additional sections: technology acceptance and use, and data management.

The second part of the questionnaire includes 28 statements adapted from the 7 constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT) model by Venkatesh et al. (2003), assessed on a 0–10 Likert scale. In the third stage, the Master Data Management Maturity (MD3M) model by Pietzka (2012) was used, with 65 questions distributed across 13 focus areas. Seven areas that did not require advanced technical knowledge and were perceptible to end users were selected. Their 35 questions were adapted to facilitate understanding for individuals who do not work with technology and to avoid an excessively long questionnaire. For each focus area, a targeted question was created, and the corresponding items—already associated with one of the five maturity levels—were adapted as response options. The levels are: Initial – awareness of data management exists; Individual – individual actions are taken to solve specific issues; Collaborative – several initiatives exist and collaboration between areas begins; Managed – defined processes and best practices in data management are in place; Optimized – data management is optimized, improving organizational efficiency.

With the approval of the Ethics Committee (opinion no. 6,774,087), Phase 2 of the survey began with a pre-test conducted with employees from other departments. Due to the small number of participants, the questionnaire was administered to the Quality and Production departments involved in the action research, constituting a non-probabilistic sampling, as its elements were intentionally selected.

The data collection was carried out between July 16 and 19, 2024, with the individual administration of the questionnaire during working hours and the final phase of the action research. The researcher explained the objectives and conditions outlined in the Free and Informed Consent Form (FICF), providing two copies of the form before inviting the employees to participate, respecting everyone's preferred response format. All employees participated in the survey by signing the FICF: 14 chose the online format and 5 the physical one.

The printed questionnaires had their responses transcribed by the researcher into the online format for grouping, after all participants had completed them. It was noted that one respondent did not select any option for one of the questions, which was recorded as "ND" (not defined). To enable statistical analysis, the data were exported from Microsoft Forms and processed in Microsoft Excel, with the creation of variables. Each question from the questionnaire was associated with a variable using a simple or compound description, joined by an underscore ("_"), reflecting its content. The variables related to the UTAUT and MD3M models followed the logic used by their respective authors and were aligned with the corresponding constructs or focus areas.

In addition to the variables related to the questions, some others had to be created to facilitate the analysis. For each construct, an average variable was generated based on the associated responses, allowing for the synthesis of acceptance levels. Additional variables were additionally created to transform nominal data into ordinal data, with scores assigned according to the responses, enabling statistical analyses. To facilitate correlational analyses, a composite variable was created that sums up the levels of participation in analysis meetings and training sessions.

The descriptive statistics and percentage calculations were performed using Microsoft Excel itself. The correlation calculations were performed with the help of PSPP software, version 1.6.2. PSPP is a free and open-source statistical analysis program created by GNU as a substitute for IBM's proprietary SPSS software (GNU, 2023).

The statistical method adopted was Spearman's correlation coefficient, ideal for ordinal and non-parametric data. Its interpretations were made based on the cutoff points provided by Cohen (1992, apud Lima, 2021), where positive correlations indicate a direct relationship between variables, while negative values point to an inverse relationship. These are considered strong when the absolute values are greater than 0.5; moderate between 0.30 and 0.50; weak above 0.10; and nonexistent below this limit.

RESULTS

Data Collection Implementation

According to Ritter and Pedersen (2020), Digital Transformation occurs through the use of digital data, obtained via digitization with technological support, requiring specific skills and capabilities for working with data. This study aimed to demonstrate the process of implementing data capture, considering factors from the data domain of DT under the perspective of the human-centered approach of I5.0. To achieve this goal, a DT process was initiated through action research, divided into five phases, culminating in the implementation of digital data capture in the first production line of the participating company.

In the first phase, the current situation was mapped to understand the manufacturing process, the data capture method, and the responsible parties involved. It was observed that the company produces different models of semi-finished products to serve segments A and B, varying the raw material and process arrangement, with the main difference between the segments being the physical characteristics of the raw material, such as width and thickness.

The production line has 11 semi-automatic machines, distributed across five distinct processes, which are adjusted, supplied, and monitored by operators. To minimize setup time, the use of equipment was standardized according to the product segment, considering the adjustments required by the variations in the raw material.

As shown in Figure 5, data collection was done using six forms in the form of inspection checklists at seven distinct points on the line during the production process, filled out by operators and inspectors. It was possible to detect data history losses, missing entries, and difficulty accessing some information due to the use of printed forms for certain checklists.

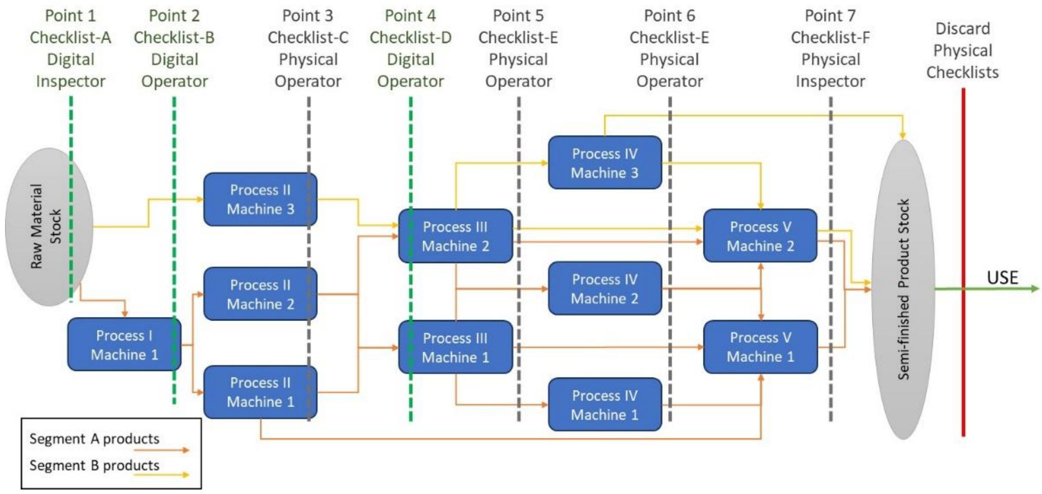

Figure 5 – Initial situation

Each form was individually evaluated during the second phase. All 108 identified fields were classified into 4 distinct groups to facilitate analysis: general descriptions and identifiers; model specifications; information during inspection; product inspection/verification. With the identification of 51 unique attributes, it was possible to notice that the information with the most redundancies was related to general descriptions and product model specifications.

During the interactions, it was observed that there were different understandings among employees regarding the inspections conducted and why they are necessary, as well as questions about the required quality parameters and their tolerances. It was necessary to explore the attributes related to the master data of the semi-finished products. The 178 attributes listed in the Product Control Plan (PCP) of the products belonging to this production line were furthermore evaluated.

During phase 3, joint analyses were conducted to evaluate each form individually, prioritizing fields related to quality inspection data and machine parameters. Divided into 4 stages, all participants in the research were invited to take part in the analysis of the identified attributes, which align with the needs of the participating company, as it was understood that they hold the domain knowledge being researched. The use of the company's intellectual capital through the involvement of its employees aligns with the goals of I5.0, which aims to shift the focus to human beings, acknowledging their knowledge and skills, as highlighted in the literature review of this research.

The initial list for analysis contained 54 fields, and after debates and knowledge exchanges, it was finalized with 76 fields. At this point, it was decided to create a new form at a point where there was none, and it was established that each data collection point should have its specific related form. For each field, its standard name, type, required fields, and its necessity in the final report printed and made available to the second production line were determined.

Phase 4 did not follow a specific methodology or maintain a pre-established schedule, being carried out in parallel and starting during the development of phase 2. It followed some assumptions related to OODs, such as the integration of data and set associations, with the main decision being the use of the company's existing ERP system. This required adaptations for its proper functioning, causing delays in the final implementation. In addition to the adaptations made to the system, other needs identified during interactions with employees were addressed, such as the relocation and acquisition of IT equipment for this project, totaling R$ 9,575.68.

In the final phase of the action research, the quality data collection was implemented in a fully digital format. Key users tested the registered checklists, contributing with improvements and additions. The creation of three new forms was necessary, totaling ten digital checklists. A final report was developed to gather the main information from the production process and make it physically available with the semi-finished products, facilitating their selection in the next stage of production. During the technical delivery to the supervisors, the final implementation status was presented (Figure 6), and no further demands for changes or adaptations were made, indicating that the implementation met the company's current needs.

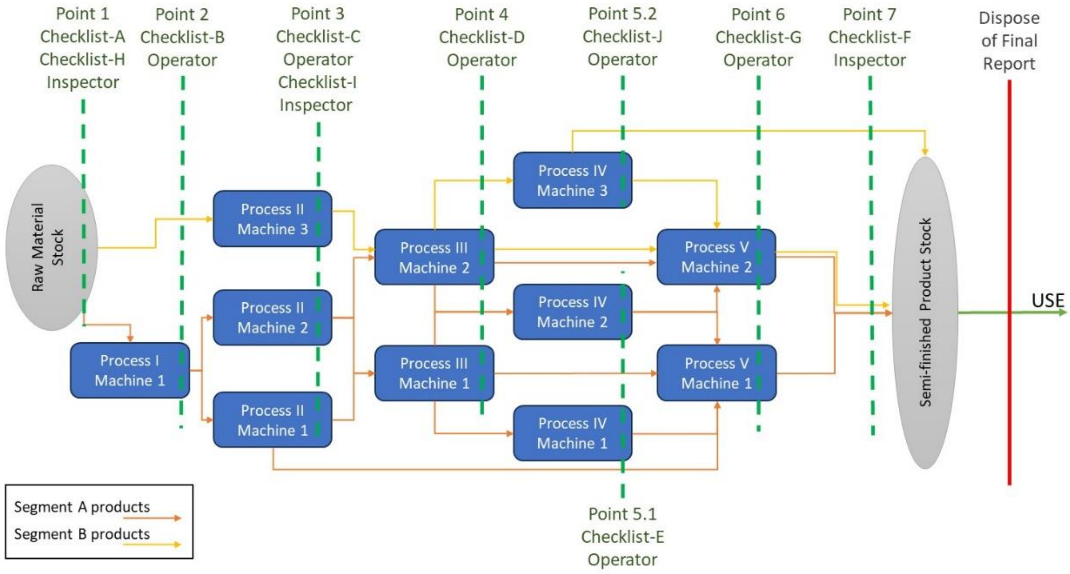

Figure 6 – Final situation

According to Hupperz et al. (2021) and Kayabay et al. (2022), making a company data-driven requires the development of technical and analytical skills to work with data, integrated with knowledge of specific domains, with employee training strategies being essential. This need is likewise reinforced in the human-centered approach of I5.0, which, as stated by Alves et al. (2023) and Longo et al. (2020), requires the active participation of workers in digital transformation, demanding continuous training and multifunctional skills.

During the action research, this approach was present at various moments, aiming to empower employees to face the challenges posed by structural and cultural changes. According to Lu et al. (2022), the human-centered approach emphasizes the centrality of the human being, including their need for belonging and interpersonal relationships with collaborative connections. Therefore, training sessions and analysis meetings were held in comfortable and motivating environments, promoting well-being, learning, and interaction among employees. In the interactions conducted during the first three phases, it was possible to observe behaviors, feelings, and some important points based on the reactions of the employees, which were:

- Lack of understanding about the need for certain forms;
- Resistance to change from some employees;
- Apprehension regarding the adequacy of the existing infrastructure;
- Doubts about adapting to new technologies, due to the individuality of each employee;
- Concerns about the impact on task execution time;
- Different reactions between those who knew the study's objectives and those who did not during the initial mapping;
- Reluctance to share information;
- Disagreements in understanding between departments and shifts;
- Uncertainties about the feasibility of the change;
- Uncertainties regarding the need for cultural transformation;

- Opinions and judgments being expressed inappropriately at improper moments, leading to unproductive discussions;
- Operators expressed doubts about their freedom to contribute and how their opinions would be considered.

The concerns of the operators related to the openness in expressing their knowledge and the fear of sharing information may indicate a non-collaborative organizational culture and a rigid hierarchical structure, which were some of the challenges of this research. In the theoretical training sessions offered between phases 1 and 3, held to overcome challenges related to the gap between operational and analytical functions (Kayabay et al., 2022), the participants themselves recognized the need for a cultural change for the success of the project.

The third phase of the action research was marked by the highest level of interaction among those involved. Despite different communication levels, most employees actively participated in the meetings, even outside regular working hours, with focused discussions and rich knowledge exchanges that enabled the reformulation of the forms, deepening the understanding of their true importance.

Although it was the most challenging phase, as it required the engagement of various departments for its execution, this phase was essential for consolidating data collection in digital format, since resistance to change was no longer observed from that point on. According to Lu et al. (2022), empathetic and respectful relationships strengthen trust and personal acceptance, unlocking growth potential and a sense of purpose, thus promoting genuine engagement in operational activities.

The acceptance of change facilitated the implementation of digital forms in phase 5, with its influence evident in the speed at which the digital forms were operationalized with users. To address the challenge of lacking technological skills (Margherita and Braccini, 2021), practical training sessions on using the digital forms were conducted individually or in small groups, directly in the employees' work environment.

Digital acceptance and influences of the human-centered approach

The collected data allowed for the characterization of the participants involved in the action research, composed exclusively of men, with 21% from the quality department and 79% from production. As shown in Figure 7, most employees are between 31 and 40 years old, with the majority having completed high school, technical education, or higher education. The length of employment ranges from 1 to over 10 years, and in both departments, most employees have been with the company for less than 5 years, with a predominance of those with 3 to 4 years of service.

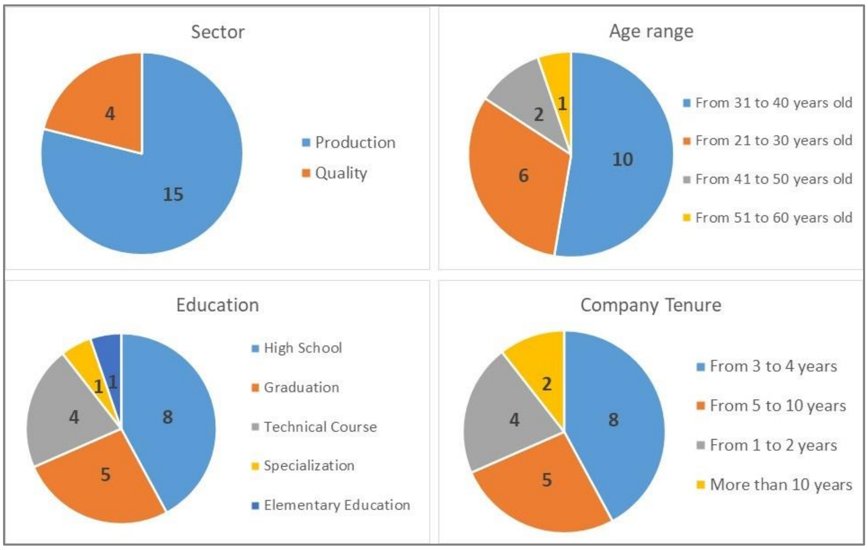

Figure 7 – Characterization of those involved

As shown in Figure 8, most employees fully participated in the training sessions and analysis meetings, representing 74% and 79% respectively. A transition in the data collection method during the questionnaire application was also observed: 63% combined the use of the system with the old checklists, 32% of respondents were already using only the system, and 5% were still exclusively using the checklists.

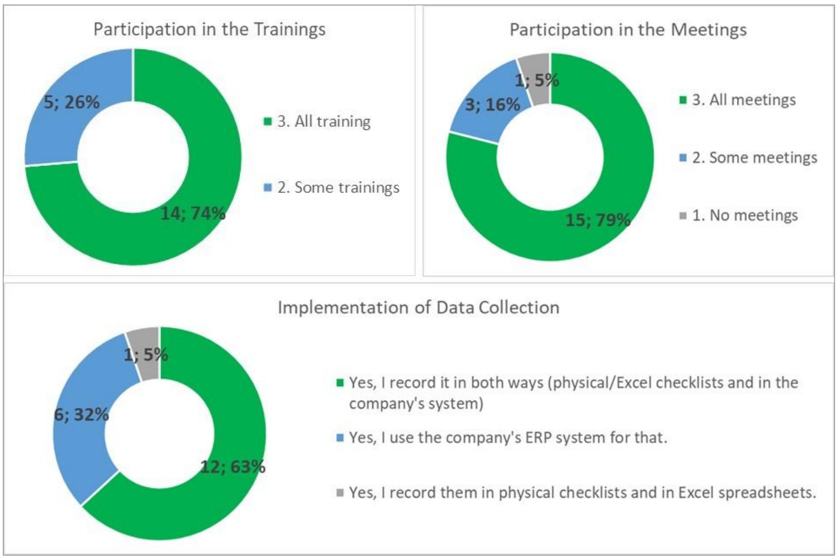

Figure 8 – Level of participation and improvement

To identify the level of technology acceptance, the averages of the constructs proposed by Venkatesh et al. (2003) were analyzed, as they directly influence the intention to use and the actual use of technology: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). According to the authors, the constructs are considered valid when their averages exceed 70%. Although the model includes four moderators, only the age variable was used in this analysis. The others — gender, experience, and voluntariness — were excluded due to limitations in data collection: lack of gender variation, the need for longitudinal application, and the mandatory use of the new technology, respectively.

Based on Figure 9, it can be observed that the new data collection format was well accepted by all employees, with averages above 87% across the main constructs. The highest level of acceptance was found among employees aged 41 to 60 from both departments, while the lowest level was recorded in the quality department, among employees with an average age of 35. "Effort Expectancy" and "Facilitating Conditions" were the highest-rated constructs, indicating employees' perception of ease of use, adequate infrastructure, and organizational support. On the other hand, "Performance Expectancy" had the lowest overall score, with 77.5% among employees in the quality department.

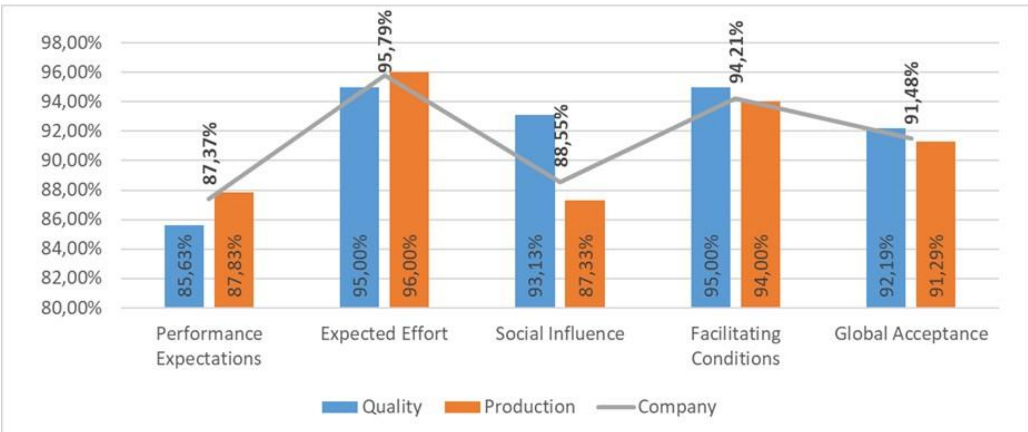

Figure 9 – Acceptance and use of technology

Through the descriptive statistical analysis of all variables in the UTAUT model, it is possible to observe that some variables may have been positively influenced by the way the action research was conducted. These variables are related to: agreement with the technology used; organizational support; support from the leaders involved; the presence of a facilitator to answer questions; ease of learning; the usefulness of the technology for work activities;

clarity of information; mastery of the knowledge required to use the technology; and perceived insecurity.

These results reflect the positive effects of the participatory approach adopted in the action research, which included targeted training sessions, openness to suggestions, infrastructure improvements, and direct support from supervisors and the company. The clear objective of improving quality data contributed to the perceived usefulness of the implemented technology, while the small-group training format was reflected in the average scores of the variables related to learning.

However, some employees still showed difficulty in understanding the overall process and, although the average scores were high, certain variables related to the technology and data integration showed greater variability in responses, suggesting areas for improvement. The greatest point of disagreement among respondents was regarding being recognized by managers through the use of technology.

The assessment of the maturity level in data management was carried out to measure the capabilities and skills developed during the action research. However, the maturity levels could not be identified due to difficulties in understanding the rule used by Pietzka (2012)to determine whether a capability was implemented or not based on the questionnaire responses. The study does not clearly state how many people answered the questionnaire or how these responses relate to confirming whether the capability being evaluated was implemented. Nevertheless, based on the distribution of responses presented in Figure 10, it is possible to identify some improvements and opportunities for enhancement in the data management of the co-participating company.

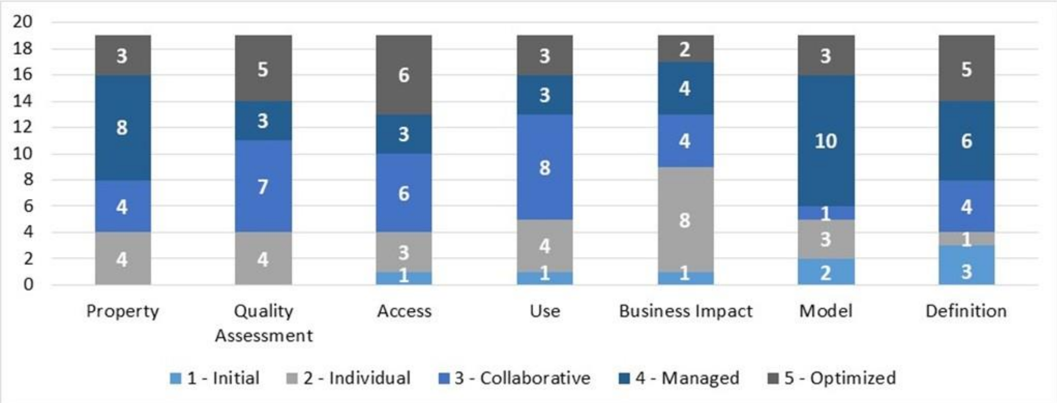

Figure 10 – Distribution of responses by management level

The areas with the greatest development are "Data Ownership" and "Data Quality Assessment," with no employees at the initial level. This indicates that everyone understands there is a person responsible for the forms, knows how to fill them out correctly, and recognizes the impact of failures in this process. The "Master Data Model" stands out with 52% at the Managed level demonstrating clear evidence that the processes are well defined, although there are still some uncertainties from certain employees, likely due to the transitional phase of the action research.

The "Data Access" area shows a greater distribution of responses across the maturity levels, possibly linked to the perception of the availability of computers for ERP use. "Data Usage" has an intermediate evaluation, with most employees understanding where to find information and receiving training when changes occur.

"Master Data Definition" similarly shows significant variation, with employees at both the highest and the initial levels, highlighting a gap in understanding the concept and demonstrating the need to standardize the knowledge of those involved. On the other hand, "Business Impact" has the lowest maturity level, with most responses at the individual level. Although employees are aware that failures can lead to losses, they may still not receive clear information on how and when this happens, demonstrating the need for greater awareness of this focus area.

To deepen the analysis of the influences that the human-centered approach had on the data collection implementation process, correlations were made between the data gathered in the survey without starting from any predefined hypothesis. Figure 11 presents the 10 most relevant correlations between the variables of the UTAUT and MD3M models and the three variables containing the participation levels.

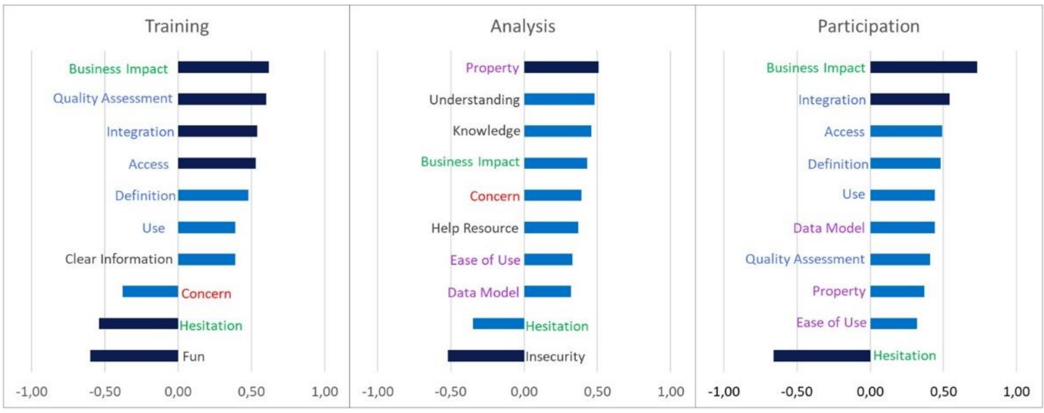

Figure 11 – Correlations between variables

The training sessions had a positive impact on employees' understanding regarding the clarity of information and ease of use. Additionally, it showed a strong relationship with the evaluation of quality, level of integration, data access, and master data definition, indicating that with greater training opportunities, employees' perception of data integration will improve, as well as their ability to enter and access the data correctly.

Although it raised some concern, the analysis meetings were essential, not only facilitating the understanding and knowledge required for the use of the technology but especially enhancing employees' comprehension of data management, including understanding the model of the analyzed data sets and their ownership. Overall participation in the meetings provided positively contributed to understanding the impact that the lack of accurate data can cause to the company.

Although the analysis meetings caused greater concern among employees, possibly related to the fear of losing data, the training sessions had a positive influence in reducing their level of concern. The inversely proportional correlations in the variables related to Hesitation and Insecurity may indicate that using a human-centered approach in TD processes, with active participation from employees and support from both the organization and its leaders, helps reduce fear and hesitation, triggering a sense of confidence and thereby reducing anxiety regarding the use of digital technologies.

CONCLUSION

This study analyzed the initial implementation of DC n in an industrial environment under the human-centered approach of I5.0, from the initial mapping to the digitization of data collection. It also evaluated the acceptance of those involved, the maturity of data management, and the influences of this approach on the process. The digitization of quality data collection in the first production line provided the company with quick access to detailed batch histories with integrated data. The analysis of essential attributes at each production stage improved the understanding of quality and its impact on the production chain. Integration with the ERP system generated new insights and business opportunities, such as quality certificates to enhance customer trust.

The study identified common challenges in digital transformation (DT) processes, such as uncertainties about adaptation, lack of understanding of objectives, hierarchical rigidity, and concerns related to infrastructure and organizational culture. The researcher faced difficulties mediating between supervisors and the IT team, who shifted responsibilities, along with a constant need for motivation. Operational areas struggled to communicate their needs, while IT showed resistance to new solutions. Furthermore, there was insecurity in sharing information and individual tensions, making the process even more challenging.

To overcome the challenges, employees were involved in the process and participated in training to develop analytical and technological skills. The human-centered approach facilitated the adaptation to digital and data-handling competencies, standing out as an effective way to ensure a sustainable and inclusive transition, where human development is just as important as technological adoption.

Venkatesh et al. (2003) highlight the importance of understanding user acceptance to achieve successful technological implementations, identifying the factors that influence it and enabling its efficient use to drive process improvements, innovation, and organizational competitiveness. With 89% acceptance, all participants acknowledged the support of the company and its leadership. In phase 3, even a previously resistant employee pointed out the success of the study before its completion, reinforcing the importance of collective construction. The survey results showed that a more human and empathetic approach created a collaborative environment, reducing resistance to change and lowering anxiety. Additionally, the exchange of experiences during meetings facilitated technology adaptation, resulting in a more sustainable transition.

The main limitation of the study was time, as digital transformation processes are complex and continuous, requiring constant adjustments and taking longer than initially expected. The combination of DT and I5.0, being broad and interdisciplinary topics, made it difficult to deepen the theoretical analyses. Additionally, the lack of specific maturity models for I5.0 and the ambiguity in interpreting the maturity levels of the MD3M model may have hindered the identification of important variables related to people's involvement and the development of data-management capabilities in the project.

Among the main findings are the correlations between technology acceptance, data management, and participation in the action research meetings, which deepened the understanding of the influences of the human-centered approach. These correlations suggest that training and collaborative meetings have a positive impact on the success of digital transformation processes. As an applied study, with an explanatory approach and inductive method, it paves the way for further research on the human-centered approach in data collection.

Future research could analyze the phases of this action research using Lu et al.'s (2022) industrial human needs pyramid and Nonaka and Takeuchi's (2008) knowledge spiral, as well as investigate the impact of education levels on data management maturity. Future studies can also be conducted within the same co-participating company to demonstrate how data collection has influenced the organization's sustainability and resilience, the other two pillars of I5.0. Other studies could evaluate digital transformation processes while considering psychological aspects to better analyze people's perceptions and the impact of technology, in addition to developing specific models to measure participation. The implementation of other stages of data collection with the human-centered I5.0 approach, including data maintenance and storage policies, could also be explored.

Conducted in a company with semi-automatic machines operated by humans and featuring, as an innovative aspect, insights gathered from interactions during the implementation, this study showed that digital data collection can be implemented without the initial installation of additional sensors by using the technologies already available in the organization. The findings highlight the essential role of workers in Digital Transformation and reinforce the need to develop technical and analytical skills for a sustainable and inclusive transition, as pointed out by authors such as Dikhanbayeva et al. (2020), Fischer et al. (2023), Hupperz et al. (2021), Kayabay et al. (2022), Ritter and Pedersen (2020), Rogers (2017), and Vial (2019).

Thus, the action research phases defined and developed in this study, when applied through the human-centered I5.0 approach, can serve as a replicable roadmap for any company to conduct its DT processes starting from structured data collection. This roadmap helps optimize information capture and support decision-making, regardless of the industry. However, its potential is especially relevant for small and medium-sized enterprises, which rely heavily on their employees as key assets and can benefit from a clear, practical, and adaptable methodology to advance toward digitalization.

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Authors contributions: IPL: Conceptualization, Methodology, Investigation, Formal Analysis and Writing - original draft. MCM and CKY: Supervision, Validation and Writing - review & editing.

Appendix

Questionnaire		
Section	**Question**	**Collection Format**
1 Characterization	Biological sex	Multiple Choice
	Age	Multiple Choice
	Education level	Multiple Choice
	Select your department	Multiple Choice
	How long have you been working at the company?	Multiple Choice
	Do you use the company's ERP system during your activities?	Dichotomous Response
	Do you check the specifications of materials and machine parameters?	Dichotomous Response
	Do you record the values found during the inspections?	Multiple Choice
	Did you receive training during the implementation process of the system for recording and controlling quality parameters?	Multiple Choice
	Did you participate in the process of defining the product/process attributes that are checked and recorded during and/or after the manufacturing of the semi-finished product?	Multiple Choice
2 Technology Acceptance and Use	I consider the system useful for recording the values found during the inspections of product specifications and machine parameters.	Likert Scale
	I believe that using only the system to record the inspections makes my activities faster.	Likert Scale
	I believe that using only the system to record the inspections will increase my productivity.	Likert Scale
	I believe that using the system increases my chances of being recognized by my managers.	Likert Scale
	The information in the system is clear and understandable, and it makes my interaction easier.	Likert Scale
	I believe it was easy for me to understand and learn how to use the system during its implementation.	Likert Scale
	I think the system is easy to use.	Likert Scale
	I was able to easily learn how to operate the	Likert Scale

	system to record the values found during the inspections I perform.	
	I consider using the system to record the inspection values a clever idea.	Likert Scale
	I believe that using a system makes my job more interesting.	Likert Scale
	I think using the system is enjoyable.	Likert Scale
	I like using the system to record the values found during the inspections of product specifications and machine parameters.	Likert Scale
	The people who influence my behavior think that I should use the system to record my inspections.	Likert Scale
	My family and people who are important to me think that I should use the system to record my inspections.	Likert Scale
	The company's management has been helpful and has supported me in using the system whenever I need it.	Likert Scale
	Overall, the company is supporting me in using the system.	Likert Scale
	I have all the resources necessary to access and use the system when I need to make my entries.	Likert Scale
	I have the necessary knowledge to use the system and record the values found during the inspections.	Likert Scale
	I notice that the system is integrated with other systems and/or tools that I use to perform my activities.	Likert Scale
	There is a person available to help me when I have difficulties using the system.	Likert Scale
	I believe I could complete my activities using the system more easily: – if there is no one nearby to tell me what to do while I perform the task.	Likert Scale
	I believe I could complete my activities using the system more easily: – if I can call someone for help in case I have difficulties.	Likert Scale
	I believe I could complete my activities using the system more easily: – if I have plenty of time to enter the values found during the inspections calmly.	Likert Scale
	I believe I could complete my activities using the system more easily: – if I have access to the system's built-in help resource.	Likert Scale
	I felt worried and apprehensive during the system implementation.	Likert Scale
	I am concerned that I might lose information if I do something wrong while using the system.	Likert Scale
	I hesitate to use the system because I am afraid of making mistakes that I cannot	Likert Scale

	correct.	
	I feel intimidated by the system and insecure about using it.	Likert Scale
3 Data Management	How do you assess your understanding of the company's Master Data?	Multiple Choice
	How do you evaluate the templates/forms containing the data attributes you use in the company today?	Multiple Choice
	How do you evaluate the quality of the information you record on the forms during your activities?	Multiple Choice
	Do you know what impact the company faces when the forms are not filled out or when the data is recorded incorrectly?	Multiple Choice
	How do you access your network files and system functions?	Multiple Choice
	Are you familiar with the forms used in the company? Is there someone responsible for managing them and helping when needed?	Multiple Choice
	Are you able to find the data easily and quickly you need to use in your activities in the department?	Multiple Choice