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# DIGITAL TRANSFORMATION OF THE SUPPLY CHAIN IN THE RAW MATERIALS AREA: A CASE STUDY FOR FMS FACTORY

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***Abstract:*** *This paper examines the impact of digital transformation on the order flow in the raw materials (RM) area of the FMS factory, which specialises in the production of custom-made men's suits. The purpose of the research is to evaluate how the implementation of digital solutions optimises processes, reduces repetitive errors, and increases transparency in raw materials management. All of these factors contribute directly to improving organisational performance. The study combines a quantitative analysis, based on data collected between January 2024 and April 2025 (order entry, processing, and output times), with a qualitative analysis using questionnaires administered to employees who worked with both the old and new flows. Using a mixed-methods approach, the research compares the previous flow, based on limited IT systems, with the digitised flow implemented in September - October 2024, testing hypotheses related to reduced processing times, decreased errors, and increased transparency, while also exploring employee perceptions. The expected results indicate a reduction in processing times, fewer errors, and better order tracking. Altogether, these findings highlight the benefits of digitalisation and provide a starting point for future strategies in the textile industry.*
***Keywords:*** *digital transformation, supply chain, raw materials, textile industry,* ANOVA analysis

## 1. INTRODUCTION

The research topic, focused on the digital transformation of the order flow within the Raw Materials (RM) sector of the textile industry—specifically in the context of custom-tailored men's suit manufacturing—is grounded in prior professional experience in production resource management within the organisation. It was observed that the combination of manual processes and complex information systems currently used at the FMS factory, specialised in made-to-measure suit manufacturing, leads to delays, errors, and resource waste. These issues negatively impact operational efficiency and customer satisfaction. Such challenges highlight the need for modernisation through digitalisation, aimed at optimising operational flows, enhancing accuracy and traceability, and ensuring market competitiveness.

The relevance of the topic is reinforced by global Industry 4.0 trends, which are reshaping the textile sector through the integration of technologies such as mobile applications, QR codes, IoT systems, and cloud-based platforms. These technologies enable both operational and organisational agility [1]. This research emphasises that digital transformation enhances existing performance while supporting continuous adaptation to market changes, thus influencing organisational competitiveness. In the realm of customised production, where efficiency, precision, and delivery times are critical, the digitalisation of the order flow at FMS addresses these requirements by reducing errors, delays, and resource waste.

The aim of this research is to evaluate the impact of digital transformation on the order flow within the Raw Materials (RM) area of the FMS factory, by comparing operational performance and employee perceptions between the initial workflow (January–September 2024) and the digitised workflow (October 2024–April 2025).

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The general objective is to analyse the impact of implementing a digitised system in the Raw Materials (RM) area of FMS.

The specific objectives are as follows: O1 - To perform a comparative evaluation of processing times (Hypothesis H1), including cutting time (Hypothesis H2), error rates, and the percentage of delayed orders (Hypothesis H3) within the RM area, by analysing data collected between January 2024 and April 2025. O2 - To assess employee perceptions regarding the efficiency and usefulness of the digitised system (Hypothesis H4), through an exploratory methodology based on questionnaires administered in May 2025.

The research Methodology adopts a mixed-methods approach, integrating both quantitative and qualitative components. For Objective O1, internal operational data from FMS were analysed for the period between January 2024 and April 2025. *Processing times* (H1) were compared using one-way ANOVA in SPSS version 22, while *Error rates* (H2) and *Delayed orders* (H3) were assessed directly from the Excel database using descriptive statistical analysis based on average values. For objective O2, four customised questionnaires were distributed to 13 employees working in the RM area (including fabric scouts, cutters, thermal press operators, and area supervisors). Responses were evaluated using a 5-point Likert scale (from 1 to 5). This methodology enables an in-depth assessment of employee perceptions regarding the impact of digitalisation, considering both operational performance and employee experience within the FMS factory.

The results indicate that the implementation of the digitised workflow has led to significant improvements: the total order processing time decreased by 83,6%, from 8434,42 minutes in the Initial workflow (P1) to 1382,28 minutes in the final Digital workflow (P3). The operational error rate decreased by 4,27%, from 6,83% in the initial phase (P1) to 6,54% in the digitised phases (P2 + P3). However, a slight increase in errors was noted in P3, suggesting the need for ongoing optimisation. The percentage of delayed orders was reduced by 43,44%, from 26.98% in P1 to 15.26% in P2 + P3, indicating improved process management.

Employee satisfaction increased, reaching an overall average of 4,08 on the Likert scale, with area supervisors reporting the highest satisfaction level (4,75).

These findings confirm the positive impact of digital transformation on both operational efficiency and employee experience, emphasising the importance of continuous training and system optimisation—especially during peak periods - in order to maximise long-term benefits.

## 2. LITERATURE REVIEW

Digital transformation has emerged as a critical pillar in the modernisation of the textile industry, particularly in the context of customised production, where efficiency, precision, and traceability of order flows are essential. This research provides a comprehensive review of the relevant academic literature related to the research topic, focusing on the impact of digitalisation and Industry 4.0 technologies on processes within the textile manufacturing sector.

Through a systematic examination of existing studies, the chapter explores how technologies such as the Internet of Things (IoT), artificial intelligence, QR code systems, and mobile applications contribute to the optimisation of workflows in the Raw Materials (RM) area, the reduction of operational errors, and the enhancement of both sustainability and competitiveness.

Moreover, the literature review identifies existing gaps in the current body of research and discusses the relevance of these findings to the FMS case study, thereby establishing a solid theoretical foundation for analysing the impact of digital transformation on the order flow within the RM sector.

The digital transformation of the textile industry, supported by Industry 4.0 technologies, has been widely studied for its capacity to enhance operational efficiency, sustainability, and competitiveness. According to [2], digitalisation in the Dutch textile and apparel industry significantly contributes to sustainability performance by improving traceability, transparency, and predictability across supply chains . Technologies such as IoT and artificial intelligence enable the monitoring of resource consumption and material types, thus reducing environmental impacts such as $CO_2$ emissions and water usage, while also addressing social indicators like safe working conditions. However, the study emphasises that digital transformation remains underutilised due to high implementation costs and the need for collaboration among both internal and external stakeholders [2]—a challenge that closely mirrors FMS's efforts to digitise its raw materials order flow.

Similarly, [3] investigates the influence of Industry 4.0 technologies on the German textile sector, highlighting their potential to address global competitiveness and labor-related challenges. The study identifies opportunities such as improved working conditions, sustainable regional production, and the use of artificial intelligence and predictive maintenance to increase efficiency. Nonetheless, barriers like a shortage of skilled labour, high investment costs, and insufficient digital infrastructure hinder adoption, particularly for SMEs. These insights are directly applicable to FMS, where mobile applications and QR code integration aim to eliminate inefficiencies caused by manual processes.

The [4] explores the application of machine learning (ML) in predicting supply chain disruptions within the textile sector. Their case study of "ABC Company" demonstrates that ML algorithms—particularly Support Vector Machines (SVM) - can efficiently predict delays, thereby improving supply chain resilience. This is directly relevant to FMS's digitised workflow, which seeks to reduce delays and operational errors in raw material processing through real-time tracking and data-driven decision-making.

The Textile Learning Factory 4.0, described by [5], offers a practical model for training and implementing Industry 4.0 technologies in the textile sector. By simulating an end-to-end production process—from online order reception to final product delivery—the factory produces custom smart bracelets. This process combines lean principles with digital tools such as IoT and Radio-Frequency Identification (RFID). RFID technology, which uses radio waves to track tagged objects, enables real-time monitoring of materials and products, thus enhancing traceability and reducing errors. This model supports FMS's initiative to reorganise its raw materials area, which includes over 2,500 new unique locations, and to train staff in the effective use of digital tools.

The [6] emphasise the role of circular open innovation and Industry 4.0 in achieving digital sustainability. Their study illustrates how IoT can trace the lifecycle of textile products, supporting reuse and recycling efforts, aligning with FMS's goal to minimise waste through digitalisation. The concept of circular ambidexterity, which balances the optimisation of current processes with the development of innovative circular business models, underscores the need for FMS to integrate digital tools with sustainable practices.

The [7] propose a methodology for generating digital human body models using 3D scanning in the textile industry, facilitating mass customisation in clothing production. By reducing product returns (by up to 30% in online sales) through precise measurements, this approach supports FMS's focus on custom-made men's suits, where accurate material processing is critical. The study's emphasis on data standardisation and cloud storage resonates with FMS's implementation of digital applications for order tracking and inventory management.

The [8] address the human factor in digital transformation, highlighting the importance of employee trust in both technology and co-workers to ensure successful adoption. Role conflicts, such as conflicting tasks between legacy and new systems, may hinder progress, emphasising the need for adequate training at FMS to align staff with the new digital workflow. In the same vein, [9] explores the role of digital twins, digital threads, and digital mindset in facilitating transformation. Digital twins are virtual representations of real-world objects or processes, used to simulate and optimise activities such as process testing before deployment. A digital thread is a system that connects data related to a product throughout its lifecycle, fostering cross-departmental collaboration. A digital mindset reflects employees' openness to adopting technologies such as AI and data analytics to explore new opportunities. These concepts directly support FMS's efforts to streamline order flow and enhance interdepartmental collaboration via digital tools.

The [10] analysis of the optimal timing for digital transformation, identifying key factors such as capital availability, data quality, and investment costs. Their findings suggest that larger enterprises with more resources, such as FMS, are more likely to adopt digitalisation early; however, high costs and data volatility may delay implementation. This supports FMS's strategic investment in digital tools and infrastructure reorganisation.

Finally, [11] emphasises the role of organisational culture in enabling digital transformation and product innovation. An adhocracy culture, characterised by flexibility, innovation, and rapid adaptability to change, is seen as most conducive to digitalisation. This culture promotes experimentation and the rapid adoption of new technologies, aligning with FMS's need to foster a culture that supports agile implementation of digital tools and employee training to enhance operational efficiency.

While the reviewed literature provides a solid foundation for understanding digital transformation in the textile industry, several gaps remain that are particularly relevant to the FMS case. [2] Moreover, [3] addresses themes such as sustainability and competitiveness. Yet, they do not specifically examine the challenges associated with raw materials order flow management in customised production, where speed and precision are critical.

The practical applications of machine learning and training models explored by [4] and [5] do not delve into the integration of mobile applications and QR codes for real-time tracking of raw materials - an approach implemented at FMS. Furthermore, the literature tends to underestimate employee perceptions of digital tools in small-scale textile operations ([8] [11], a dimension explicitly addressed through the qualitative analysis of employee satisfaction at FMS.

Although economic and logistical barriers to adopting advanced technologies - such as 3D scanning [7] or blockchain [6] - are acknowledged, their implications are not fully explored in the context of SMEs with limited resources. The FMS case study fills this gap by demonstrating cost-effective digitalisation strategies, such as the use of mobile applications and QR codes, tailored for smaller firms.

The relevance of these studies to FMS lies in validating the potential of digitalisation to reduce errors, delays, and waste, while simultaneously enhancing employee satisfaction and operational efficiency [12][13]. Emphases on training [5], trust [8], and organisational culture support FMS's approach of combining technological upgrades with workforce development. By addressing these identified gaps, this study contributes to the academic literature through a data-driven, mixed-methods analysis of digital transformation within a specialised textile production environment.

## 3. METHODOLOGY

The study adopts a mixed-methods approach, combining quantitative analysis of operational data with qualitative analysis of employee perceptions, to assess the impact of digitalisation on the order flow in the RM area of the FMS factory. Data were collected between January 2024 and April 2025, covering both the previous flow (January–August 2024) and the digitised flow (September 2024–April 2025).

### 3.1. Quantitative Data Collection

The quantitative data come from FMS's internal systems, including Navision (for the previous flow) and dedicated digital apps used by finders, cutters, and heat calender operators (for the digitised flow). Key indicators are: Entry Time = the moment the order is registered in the RM area. Processing Time = duration until the fabric cutting is validated. Exit Time = when the fabric is scanned at the industrial heat calender to assign the preparation batch. Error Rate = frequency of issues such as: missing fabric rolls, duplicate orders, or lost files. Transparency = the ability to detect delayed orders without client intervention.

### 3.2. Qualitative Data Collection

A questionnaire was administered to employees who operated in both periods (pre- and post-digitalisation) to assess their perceptions of efficiency, transparency, and satisfaction. The sample included 13 employees: 4 finders, 4 cutters, 3 heat calender operators, 2 area managers.

The questionnaire had closed questions on a Likert scale (1 = Strongly Disagree, 5 = Strongly Agree), structured into four sections, each tailored to the specific responsibilities of the role. Each section had 4 questions, totalling 16 questions, assessing: Finders, Cutters, Heat Calender Operators and Area Managers.

The questionnaire was administered in physical format in May 2025, with each employee completing only the section relevant to their role. The response rate was 100%, supported by anonymity and personalised distribution.

The performance of the previous flow is compared to the digitised one based on the quantitative indicators. Qualitative data are used to contextualise quantitative results and identify subjective factors influencing performance.

Three quantitative hypotheses were formulated:

The H1 hypothesis: The implementation of the digitised workflow leads to a decrease in the average processing time of an order in the Raw Materials (RM) area.

This hypothesis reflects a central premise of any digitisation effort - namely, increased operational efficiency. In the context of the FMS factory, processing time in the RM area refers to the period from when an order is introduced into the system until it exits the RM zone. In the initial workflow, the process was marked by manual steps and a lack of transparency, which led to prolonged durations: files were lost, fabric bales were searched for across multiple physical locations without an efficient tracking system, and orders were often blocked due to missing information or materials.

The H2 hypothesis: The digital workflow reduces the rate of operational errors (such as identification mistakes, stock shortages, and human errors).

This hypothesis stems from the commonly encountered reality in many sectors - human error is inevitable in manual systems. In the initial workflow, employees had to identify bales using handwritten labels, manually note fabric locations on order files to ease the search, and perform other unnecessary tasks that increased processing time. This led to confusion between similar fabric codes, accidental use of materials intended for other orders, lost files among bales, and mixed-up files at the thermal calender.

The digital system in this area is designed to resolve all issues of the initial flow. Applications allow barcode or QR scanning, stock and location logging, and real-time alerts for incorrect actions. Moreover, digital tools centralise and synchronise data between teams, eliminating discrepancies between physical and digital information. H2 is vital for assessing process quality, as error rates directly impact rework, extra costs, and delays. If validated, this hypothesis will demonstrate that the digital workflow significantly reduces these errors and supports the conclusion that investment in digitisation improves process reliability and delivery consistency.

The H3 hypothesis: The number of delayed orders in the Raw Materials area decreases as a result of implementing the digitised workflow.

Delays in material preparation directly affect the entire production chain. For FMS, which operates under strict deadlines, such delays can result in late deliveries, decreased customer satisfaction, and even order cancellations. In the initial workflow, orders were sometimes blocked for several days due to stock errors or the inability to locate materials. Often, solutions were improvised, consuming extra time or requiring substitution with alternative stock.

With digitisation, orders can be easily tracked, and the system enables rapid identification of bottlenecks and prioritisation of those orders. Each factory area has a maximum allowable processing time - for RM, it is 48 hours. Therefore, this hypothesis targets a concrete and measurable outcome: a reduction in the number of delayed orders in the Raw Materials area. Confirming this would demonstrate the digitised workflow's efficiency in ensuring operational continuity and reducing vulnerabilities within the internal supply chain.

The H4 hypothesis. Employee satisfaction in the Raw Materials area increases due to improved clarity, traceability, and reduced redundant work.

Employee satisfaction is often overlooked in operational efficiency analyses, yet it is crucial here because it directly affects the adoption and stability of newly implemented processes. In the previous flow, employees were often frustrated by unpredictability, wasted time on unnecessary searches, and a lack of visibility over the entire process. These conditions hindered motivation, increased stress, and lowered engagement.

The implementation of the digital workflow not only optimises the process but also transforms how people work. Tasks become clearer, interactions faster, and information accessible from a single source. Validation of this hypothesis, supported by employee survey data, adds a valuable human dimension to the research and offers insight into the sustainable adoption of new practices and the extent to which digitalisation is integrated into the organisational culture.

These hypotheses are tested using statistical tests in SPSS, with the ANOVA method and MS Excel.

### 3.3. Tools and Techniques

Quantitative data are processed using SPSS statistical software and MS Excel, with results visualised through charts and tables. Qualitative responses are coded using the Likert scale.

## 4. EXPERIMENTAL RESULTS AND ANALYSIS

### 4.1. Description of the Order Flows

This section details the order flow used in the Raw Materials (RM) area of the FMS factory, comparing the previous system, which relied on limited IT tools, with the digitised flow introduced in September–October 2024.

The previous flow, used until August 2024, was based on IT systems like Navision, but it had insufficient functionality and a complex interface. It required advanced skills from a poorly trained staff, leading to operational problems.

Limitations of the Previous Flow are presented in Table 1.

*Table 1*

**Problems identified in the initial process**

| **Step** | **System Used** | **Frequent Issues** |
|---|---|---|
| File Generation | Manual matching and printing in Navision | Lost or duplicate files |
| Accumulation & Scanning | VTE Tracking System | Delays due to file accumulation |
| Transfer to RM | Manual | Lost files during handover |
| Roll Search | Navision location system | Rolls not found, incorrect data, or mishandling |
| Preparation for Cutting | Manual | Files misplaced among other rolls |
| Fabric Cutting | Manual entry in VTE, consumption sheet filled | Missing stock, unrecorded deductions |
| Industrial Thermal Calender | Operator Knowledge at Entry Point | The operator is not always properly informed about the types of fabrics that should not be processed through the thermal calender. |
| Exit from RM | Barcode scanned from file; internal app assigns batch | Time-consuming manual handover at the heat calender |

These issues, combined with insufficient staff training and the rigidity of the systems in use, impacted the factory's productivity and customer satisfaction, highlighting the need for a radical overhaul.

Recognising the limitations of the initial workflow, which relied on manual processes, limited IT systems, and inefficient spatial organisation, FMS Factory implemented, starting in October 2024, a modernised operational flow based on digitalisation, automation, and structural reorganisation. This new system was designed to eliminate bottlenecks, reduce human error, and optimise order processing, thereby improving internal efficiency and customer relations. The digitised workflow integrates new digital applications, barcodes and QR codes for traceability, a redesigned physical infrastructure, and automated processes, radically transforming order management both in the office and in the Raw Materials area.

### 4.2. Hypothesis testing

To validate these hypotheses, a mixed methodology was applied, combining quantitative analysis of operational data with qualitative analysis of the perceptions of employees directly involved in activities within the Raw Materials area.

The goal was to objectively assess the impact of digitalisation on the efficiency, traceability, and accuracy of internal processes, compared to the workflow prior to the implementation of digital applications.

Quantitative data was collected from FMS internal systems, including the "Navision" application (used for the initial workflow) and the dedicated digital applications used by searchers, cutters, and thermal calender operators (used for the digitised workflow).

The main indicators are: *Total time spent in the RM area* – the time calculated from when an order enters the Raw Materials area until it exits the zone; *Time until the cutting stage* – the time calculated from when an order enters the Raw Materials area until the fabric is cut; *Error rate* – the number of data errors caused by issues such as missing fabric bales, duplicated orders, lost files, etc.; *Number of delayed orders* – the delivery date of an order is calculated based on a maximum number of days it can remain in a given area. In the case of the RM area, an order is considered delayed after 48 hours from its registration in the zone.

To test the hypotheses (H1, H2, H3), internal data was used covering the period between January 2024 and April 2025.

Based on this data, the following was calculated for each order: The duration from the order's entry into the Raw Materials area (RM) until the cutting stage (in minutes); The duration from fabric cutting until the order exited the area (in minutes); The total processing time of an order from entry to exit (in minutes); The type of workflow used to process the order Initial/Digitized); The period during which the order was processed (P1/P2/P3).

The coding is as follows: P1 – initial workflow (January 1, 2024 – September 30, 2024); P2 – digitised workflow during adaptation phase (October 1, 2024 – December 31, 2024); P3 – finalised digitised workflow (January 1, 2025 – April 2025).

Testing Hypothesis H1: The implementation of the digitised workflow leads to a decrease in the average processing time of an order in the Raw Materials area.

A sample of 10,000 records was selected for each of the three periods: P1, P2, and P3, since SPSS v22 only supports up to 32,000 distinct values for a single variable (i.e., a maximum of 32,000 records).

To compare the three periods based on the averages of the three characteristics (dependent variables) - Entry-to-Cutting Duration (min), Cutting-to-Exit Duration (min), and Total Duration (min) - a One-Way ANOVA test (analysis of variance with one factor) was applied. It is important to note that the three value series are independent of one another.

The independent variable Period, structured across three levels, was converted into a numeric nominal variable with the following codes: 1 = P1, 2 = P2, 3 = P3.

The One-Way ANOVA method compares the variance between variables, analysing the following hypotheses:

H0: $\mu_1 = \mu_2 = \mu_3$ (the means are approximately equal)

H1: At least two means are different, and there is variance within the groups.

The descriptive analysis applied to the three data sets is presented in Table 2.

Table 3 indicates that the variances of the three parameters across the three periods are not equal (p-value = Sig. = 0.00 < 0.05, which means the alternative hypothesis of unequal variances is validated). This leads to applying the ANOVA method for series with unequal variances (Welch's test).

In Table 4 it can be observed that the values of the Fisher test are high and statistically significant. Therefore, we can conclude that the three periods – Initial (classic) flow, Digital flow with testing, and Digital flow – had a major impact on two characteristics: Entry/Cutting Duration and Total Flow Duration, and a somewhat smaller impact on the parameter Cutting/Exit Duration.

*Table 2*

**Descriptive Analysis on the Value Sets for the 3 Analysed Periods P1–P3**

| | | N | Mean | Standard Deviation | Standard Error | Confidence Interval for Mean (95%) | | Min | Max |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Lower B. | Upper B. | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Entry/Cutting Duration (min)** | 1 | 10000 | 7914,86 | 2,538,809 | 25,388 | 7865,09 | 7964,62 | 15 | 14428 |
| | 2 | 10000 | 2115,13 | 1,132,896 | 11,329 | 2092,93 | 2137,34 | 1008 | 4573 |
| | 3 | 10000 | 972,93 | 505,312 | 5,053 | 963,02 | 982,83 | 9 | 1747 |
| | **Total** | 30000 | | | | | | | |
| **Cutting/Exit Duration (min)** | 1 | 10000 | 519,57 | 1,439,523 | 14,395 | 491,35 | 547,78 | 1234 | 13000 |
| | 2 | 10000 | 226,96 | 1,048,947 | 10,489 | 206,40 | 247,52 | 432 | 37204 |
| | 3 | 10000 | 409,35 | 476,717 | 4,767 | 400,00 | 418,69 | 23 | 1705 |
| | **Total** | 30000 | | | | | | | |
| **Total Duration (min)** | 1 | 10000 | 8434,42 | 2,167,359 | 21,674 | 8391,94 | 8476,91 | 5816 | 14455 |
| | 2 | 10000 | 2342,09 | 1,549,379 | 15,494 | 2311,72 | 2372,46 | 1011 | 38792 |
| | 3 | 10000 | 1382,28 | 136,964 | 1,370 | 1379,59 | 1384,96 | 1203 | 1750 |
| | **Total** | 30000 | | | | | | | |

The results of applying the one-way ANOVA with unequal variances are presented in Table 4.

Since the value series do not have equal variances (Levene's test, Table 4), the Welch ANOVA method is applied. The results are presented in Table 5.

*Table 3*

**Test of Homogeneity of External Variance**

| | Levene's Test | df1 | df2 | Sig. |
|---|---|---|---|---|
| Entry/Cutting Duration (min) | 6226355 | 2 | 29997 | 0.0 |
| Cutting/Exit Duration (min) | 460297 | 2 | 29997 | 0.0 |
| Total Duration | 7977366 | 2 | 29997 | 0.0 |

*Table 4.*

**Results of One-Way ANOVA with Unequal Variances**

| | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| Entry/Cutting Duration (min) | Between | 277106055877,93 | 2 | 138553027938,96 | 52059,26 | 0,000 |
| | Within | 79835457826,954 | 29997 | 2661448,072 | | |
| | Total | 356941513704,88 | 29999 | | | |
| Cutting/Exit Duration (min) | Between | 436771412,357 | 2 | 218385706,178 | 192,706 | ,000 |
| | Within | 33994331568,371 | 29997 | 1133257,711 | | |
| | Total | 34431102980,728 | 29999 | | | |
| Total Duration (min) | Between | 292568431117,27 | 2 | 146284215558,63 | 61664,50 | 0,000 |
| | Within | 71160667473,167 | 29997 | 2372259,475 | | |
| | Total | 363729098590,44 | 29999 | | | |

In Table 7, since $p < 0.05$ for all three variables, this indicates that there are statistically significant differences between the analysed groups (parameters).

*Table 5*

Welch Test for Equality of Means

| | **Statistic** | **df1** | **df2** | **Sig.** |
|---|---|---|---|---|
| Entry/Cutting | Welch | 2 | 15883,727 | 0,000 |
| Cutting/Exit | Welch | 2 | 16573,891 | 0,000 |
| Total | Welch | 2 | 13487,981 | 0,000 |

*Table 6*

**Multiple Comparison of the Three Characteristics (Pairwise)**

| Independent Variable | (I) Period | (J) Period | Mean Difference | Std. Error | Sig. | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower B. | Upper B. |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Entry/Cutting Duration (min) | 1 | 2 | 5799,726* | 27,801 | ,000 | 5734,56 | 5864,89 |
| | | 3 | 6941,929* | 25,886 | ,000 | 6881,25 | 7002,61 |
| | 2 | 1 | -5799,726* | 27,801 | ,000 | -5864,89 | -5734,56 |
| | | 3 | 1142,203* | 12,405 | ,000 | 1113,13 | 1171,28 |
| | 3 | 1 | -6941,929* | 25,886 | ,000 | -7002,61 | -6881,25 |
| | | 2 | -1142,203* | 12,405 | ,000 | -1171,28 | -1113,13 |
| Cutting/Exit Duration (min) | 1 | 2 | 292,606* | 17,812 | ,000 | 250,86 | 334,35 |
| | | 3 | 110,219* | 15,164 | ,000 | 74,67 | 145,76 |
| | 2 | 1 | -292,606* | 17,812 | ,000 | -334,35 | -250,86 |
| | | 3 | -182,387* | 11,522 | ,000 | -209,39 | -155,38 |
| | 3 | 1 | -110,219* | 15,164 | ,000 | -145,76 | -74,67 |
| | | 2 | 182,387* | 11,522 | ,000 | 155,38 | 209,39 |
| Total duration (min) | 1 | 2 | 6092,331* | 26,642 | ,000 | 6029,89 | 6154,78 |
| | | 3 | 7052,147* | 21,717 | ,000 | 7001,24 | 7103,05 |
| | 2 | 1 | -6092,331* | 26,642 | ,000 | -6154,78 | -6029,89 |
| | | 3 | 959,816* | 15,554 | ,000 | 923,36 | 996,28 |
| | 3 | 1 | -7052,147* | 21,717 | ,000 | -7103,05 | -7001,24 |
| | | 2 | -959,816* | 15,554 | ,000 | -996,28 | -923,36 |

* *The difference between means is significant at the 95% confidence level.*

The results of the comparisons are presented in Tables 7, 8, and 9.

*Table 7*

**Entry/Cutting Duration (min)**

| Comparison | Mean Difference (I-J) | Significance |
|---|---|---|
| P1 vs P2 | +5799,73 min | Significant |
| P1 vs P3 | +6941,93 min | Significant |
| P2 vs P3 | +1142,20 min | Significant |

In conclusion, Entry/Cutting Duration is significantly longer in period P1 compared to the other two periods (Digital with testing and Digital). Period P3 has the shortest durations regarding the Entry/Cutting Duration parameter.

*Table 8*

**Cutting/Exit Duration (min)**

| Comparison | Mean Difference (I-J) | Significance |
|---|---|---|
| P1 vs P2 | +292 min | Significant |
| P1 vs P3 | +110 min | Significant |
| P2 vs P3 | -182 min | Significant |

From Table 8, it can be concluded that during period P2 (Digital flow with testing), the average time for the Cutting/Exit Duration characteristic is the lowest. This is not surprising, as the flow is digitised and there is direct human control over it.

*Table 9*

**Total Duration (min)**

| Comparison | Mean Difference (I-J) | Significance |
|---|---|---|
| P1 vs P2 | +6092,3 min | Significant |
| P1 vs P3 | +7052,15 min | Significant |
| P2 vs P3 | +959,82 min | Significant |

Table 9 summarises the information showing that period P3 (final digital flow) contributes to a reduction in supply chain processing time.

**Hypothesis H2:** The digital flow reduces the rate of operational errors.

The reference table showing the operational error rate by process period is presented in Table 10.

*Table 10*

**Data Error Analysis by Period**

| **Period** | **No. of Orders** | **No. of Data Err** | **Data Error (%)** |
|---|---|---|---|
| P1 | 148,933 | 10,171 | 6,83 |
| P2 | 37,235 | 2,258 | 6,06 |
| P3 | 77,518 | 5,244 | 6,76 |
| (P3 + P2) | 114,753 | 7,502 | 6,54 |

Based on Table 11, the percentage variations in error rates between periods are shown in Table 11.

According to Table 11, the data error rate (%) in the initial flow (01.01.2024–30.09.2024, P1) was 6.83%, based on a volume of 148,933 orders, establishing the process baseline. With the transition to the digital flow during the adaptation period (01.10.2024–31.12.2024, P2), the error rate decreased to 6.06%, for a volume of 37,235 orders—an 11.20% reduction compared to P1 (as shown in Table 13). This drop reflects the benefits of automation, reduced manual intervention, and improved data traceability in the digital system.

*Table 11*

**Percentage Variation of Data Errors Between Periods**

| Compared Periods | Percentage Variation in Data Errors (%) |
|---|---|
| P2 vs P1 | -11,20 |
| P3 vs P1 | -0,94 |
| P3 vs P2 | 11,55 |
| (P3 + P2) vs P1 | -4,27 |

According to Table 11, the data error rate (%) in the initial flow (01.01.2024–30.09.2024, P1) was 6.83%, based on a volume of 148,933 orders, establishing the process baseline. With the transition to the digital flow during the adaptation period (01.10.2024–31.12.2024, P2), the error rate decreased to 6.06%, for a volume of 37,235 orders—an 11.20% reduction compared to P1 (as shown in Table 13). This drop reflects the benefits of automation, reduced manual intervention, and improved data traceability in the digital system.

However, in the final digital period (01.01.2025–30.04.2025, P3), the error rate increased to 6.76%, for a volume of 77,518 orders, representing an 11,55% increase compared to P2 and a minor 0.94% decrease compared to P1. Thus, some of the gains achieved during the adaptation period were lost, possibly due to system overload during peak operational periods (e.g., increased order volume, temporary technical issues, etc.).

Evaluating the impact of digitalisation across the full digital period (P2 + P3), which includes 114,753 orders and 7,502 errors, results in a combined error rate of 6,54%. Compared to P1, this represents a 4,27% reduction in operational errors. In conclusion, hypothesis H2 is validated, as the total error rate during the digital period is lower than in the initial period. However, the positive effect is moderate, and the results from P3 suggest that digitalisation should be supported by complementary measures such as continuous staff training and system improvements based on feedback.

**Hypothesis H3**: The number of delayed orders in the raw materials area decreases as a result of implementing the digitised flow.
The reference table for the rate of delayed orders by process period is presented in Table 12.

*Table 12*

**Analysis of Delayed Orders by Period**

| Period | No. of Orders | No. of Delayed Orders(>48h) | Delayed Order(%) |
|---|---|---|---|
| P1 | 148,933 | 40,182 | 26,98 |
| P2 | 37,235 | 6,743 | 18,11 |
| P3 | 77,518 | 10,769 | 13,89 |
| (P3+ P2) | 114,753 | 17,512 | 15,26 |

Based on Table 12, the percentage changes in delayed order rates between periods are summarised in Table 13.

In the reference period (01.01.2024–30.09.2024, P1), the classic operational flow recorded a delay rate of 26.98% from a total of 148,933 orders. With the transition to the digital flow during the adaptation phase (01.10.2024–31.12.2024, P2), the proportion of delayed orders significantly dropped to 18,11%, marking a 32,88% reduction compared to period P1. This substantial decline indicates improved order management enabled by digitalisation.

*Table 13*

**Percentage Variation of Delayed Orders Between Periods**

| Compared Periods | Percentage Variation of Delayed Orders (%) |
|---|---|
| P2 vs P1 | -32,88 |
| P3 vs P1 | -48,51 |
| P3 vs P2 | -23,29 |
| (P3 + P2) vs P1 | -43,44 |

In the following stage (01.01.2025–30.04.2025, P3), where the digital system operated in a stable mode, the delay rate decreased further to 13.89% across 77,518 orders. Compared to P1, this represents a 48.51% reduction and a further 23.29% drop from the adaptation period (P2). These results suggest that, as staff became more familiar with the system and digital processes stabilised, efficiency in the raw materials area continued to improve.

Looking at the overall digital period (P2 + P3), the total of 114,753 orders experienced 17,512 delays, resulting in an aggregated delay rate of 15.26%. Compared to P1, this level represents a 43.44% decrease, confirming the benefits of implementing the digital solution.

In conclusion, hypothesis H3 is supported by the data analysis. The digitalisation of the operational flow in the raw materials area clearly reduced delays, both immediately during the transition and in the longer term. To maintain this positive trend, it is important to reinforce digital practices, continuously train the involved teams, and adapt workflows based on specific operational needs.

**Hypothesis H4**: The satisfaction level of employees involved in raw materials (RM) activities increases due to improved clarity, traceability, and the reduction of redundant work.

In addition to operational data analysis, the study also collected qualitative data through the application of four distinct questionnaires, each adapted to the specific roles of employees involved in the newly digitised workflow. The purpose was to capture the direct perceptions of staff regarding the changes introduced by digitalisation in their daily tasks.

The sample included all employees in the area (13 in total): 4 bale locators, 4 fabric cutters, 3 thermal calendar operators, and 2 heads of the raw materials zone. The questionnaires were completed in physical format in May 2025. All responses were anonymous, which contributed to the sincerity of the answers and resulted in a 100% response rate**.**

To evaluate the validity of Hypothesis H4, qualitative data obtained from the questionnaires were analysed. The individual results show that the overall average response score for all questions is 4,08, and the average per respondent is 4,37. These values indicate a high level of employee satisfaction, exceeding the neutrality threshold (3) and even the upper limit of moderate positive evaluation (4).

*Table 14*

**Average Scores by Job Category**

| **Category** | **Q1** | **Q2** | **Q3** | **Q4** | **Cat.Av** |
|---|---|---|---|---|---|
| Bale Locators | 5,00 | 4,75 | 4,00 | 4,00 | 4,44 |
| Fabric Cutters | 5,00 | 3,25 | 4,50 | 3,50 | 4,06 |
| Thermal Calendar Oper. | 4,67 | 4,00 | 4,67 | 4,33 | 4,42 |
| Supervisors | 5,00 | 4,50 | 4,50 | 5,00 | 4,75 |

To further detail the perceived level of improvement, Table 14 presents the average scores by occupational category, from which the following observations can be made.

Considering the values obtained from category-based responses presented in Table 15, we can conclude that Hypothesis H4 is validated. The implementation of the digitised workflow contributed to an increase in employee satisfaction in the raw materials area by improving information clarity and traceability, as well as reducing redundant work and operational effort.

## 5. CONCLUSIONS

The study carried out in this work aimed to evaluate the impact of digital transformation on the order flow in the raw materials (RM) area of the FMS factory, a company specialised in the production of custom-made men's suits.

The first objective of the study (O1) focused on a comparative evaluation of operational performance, measured by processing times, error rates, and the number of delayed orders. Hypothesis H1 testing confirmed that the implementation of the digitised flow significantly reduced the average order processing time.

Hypothesis H2, which assumed that the digitised flow reduces operational errors (identification mistakes, stock shortages), was validated, albeit with a moderate impact.

Hypothesis H3 testing demonstrated that the digitised flow significantly reduced the number of delayed orders.

The second objective (O2) of the study explored employee perceptions regarding the efficiency and usefulness of the digitised flow.

Hypothesis H4 testing confirmed a significant increase in employee satisfaction, with an overall response average of 0,8 on a Likert scale, and an average per respondent of 4.37. RM area supervisors reported the highest satisfaction, with an average of 4,75, due to enhanced monitoring and resource management capabilities.

## 6. REFERRING

[1] Clohessy, T., Acton, T., & Morgan, L. (2017). The impact of cloud-based digital transformation on ICT service providers' strategies. In A. Pucihar & M. K. Borštnar (Eds.), *Digital transformation – From connecting things to transforming our lives: Proceedings of the 30th Bled eConference, June 18–21, 2017, Bled, Slovenia* (pp. 118–121). University of Maribor Press. https://press.um.si/index.php/ump/catalog/book/234

[2] Tolentino-Zondervan, F., & DiVito, L. (2024). Sustainability performance of Dutch firms and the role of digitalisation:

The case of the textile and apparel industry. *Journal of Cleaner Production*, 459, 142573. https://www.sciencedirect.com/science/article/pii/S0959652624020213

[3] Fromhold-Eisebith, M., Marschall, P., Peters, R., & Thomes, P. (2021). Torn between digitised future and context-dependent past – How implementing 'Industry 4.0' production technologies could transform the German textile industry. *Technological Forecasting and Social* https://www.sciencedirect.com/science/article/pii/S0040162521000524

[4] Jebbor, I., Benmamoun, Z., & Hachimi, H. (2024). Forecasting supply chain disruptions in the textile industry using machine learning: A case study. *Journal of Management Analytics*, 15(12), 103116. https://www.sciencedirect.com/science/article/pii/S2090447924004970

[5] Küsters, D., Praß, N., & Gloy, Y.-S. (2017). Textile Learning Factory 4.0 – Preparing Germany's textile industry for the digital future. *Procedia Manufacturing*, 9, https://www.sciencedirect.com/science/article/pii/S2351978917301531

[6] Hadi, N. U., Almessabi, B., & Khan, M. I. (2025). Leveraging industry 4.0 and circular open innovation for digital sustainability: The role of circular ambidexterity. *Journal of Open Innovation,* 11(2), 100545. https://www.sciencedirect.com/science/article/pii/S2199853125000800

[7] Bas, G., Dönmezer, S., & Durakbaşa, M. N. (2022). A roadmap for quality of the digital human model in the textile and apparel industry enabled by digital transformation. *IFAC-PapersOnLine*, 55(39), 319–324. https://www.sciencedirect.com/science/article/pii/S240589632203083X

[8] Malik, M., Andargoli, A., Pala, K., & Tortorella, G. L. (2025). Towards explaining the effects of the human-technology dynamic on human agency in digital transformations. *IJ of Information Mng*, 84, 102915. https://www.sciencedirect.com/science/article/pii/S0268401225000477

[9] Ghosh, S., Hughes, M., Hughes, P., & Hodgkinson, I. (2025). Digital twin, digital thread, and digital mindset in enabling digital transformation: A socio-technical systems perspective. *Technovation*, 144, 103240. https://www.sciencedirect.com/science/article/pii/S0166497225000720

[10] Chen, Z., & Liang, W. (2025). The optimal timing and conditions for the digital transformation of traditional enterprises. *The N. Am. J. of Ec & Finance*, 79, 102443. https://www.sciencedirect.com/science/article/pii/S106294082500083X

[11] Cao, G., Duan, Y., & Edwards, J. S. (2025). Organisational culture, digital transformation, and product innovation. *Information & Management*, 62(4), 104135. https://www.sciencedirect.com/science/article/pii/S0378720625000382

[12] Sarfraz, M., Ye, Z.;, Dragan, F., Ivascu, L., Artene, A (2022). *Digital Transformation Strategy and Environmental Performance: A Case Study*, International Journal Of Computers Communications & Control Volume 17, Issue 6, DOI 10.15837/ijccc.2022.6.5029, WOS:000916072300009

[13] Sarfraz, M., Ivascu, L., Abdullah, MI (2022). *Editorial: Sustainable digital economy, entrepreneurship, and blockchain technology role in industrial-organizational psychology,* FRONTIERS IN PSYCHOLOGY, Volume 13,WOS:000886078200001

## Transformarea digitală a lanțului de aprovizionare în zona de materii prime: studiu de caz pentru fabrica FMS

Această lucrare analizează impactul transformării digitale asupra fluxului comenzilor din zona de materii prime (MP) a fabricii FMS, specializată în producția de costume bărbătești la comandă. Scopul cercetării este de a evalua modul în care implementarea soluțiilor digitale optimizează procesele, reduce erorile repetitive și crește transparența în gestionarea materiilor prime, ceea ce contribuie direct la îmbunătățirea performanței organizaționale. Studiul combină o analiză cantitativă – bazată pe date colectate între 01.2024 și 04.2025 (timpul de intrare, procesare și ieșire al comenzilor) – cu o analiză calitativă, utilizând chestionare aplicate angajaților care au lucrat atât cu fluxul vechi, cât și cu cel nou. Prin utilizarea unei abordări de tip metodă mixtă, cercetarea compară fluxul anterior, bazat pe sisteme informatice limitate, cu fluxul digitalizat implementat în perioada 10.2024, testând ipoteze legate de reducerea timpilor de procesare, scăderea erorilor și creșterea transparenței, explorând totodată percepțiile angajaților. Rezultatele așteptate indică o reducere a timpilor de procesare, mai puține erori și o mai bună urmărire a comenzilor. Toate aceste concluzii evidențiază beneficiile digitalizării și oferă un punct de plecare pentru strategii viitoare în industria textilă.

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