ASDS – 5301

Final Project Report

Productivity Analysis of Garment Workers

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1. INTRODUCTION:

1.1. Problem Statement:

The garment industry is one of the world's largest and most dynamic industries, yet it is still grappling with chronic problems in the optimization of workers' productivity. Productivity variations often arise due to many interacting factors, which include incentives, idle time, frequent style changes, and workflow inefficiencies. These issues affect not only operational efficiency but also the welfare and morale of workers. Understanding these factors in detail is crucial to ensure that management strategies reach the root cause of inefficiency without sacrificing worker satisfaction and engagement.

1.2. Objective:

The project aimed at understanding the factors influencing productivity in garment factory workers from an operational and workforce perspective. We try to gain insights using statistical analysis and exploratory data techniques that will help management in streamlining operations without compromising on a supportive work environment. Our aim is to provide data-driven recommendations that improve productivity, which does not compromise the well-being of workers, hence enabling a sustainable and thriving ecosystem for production.

1.3. Motivation:

Productivity within the garment industry is not just output but an end reflection of human effort in combination with operational processes and organizational strategy. The pressure for efficiency from industries across the world has risen, creating a dire need for empowerment among garment workers and the dispersal of barriers. This project is driven by the need for positive change: to seek out patterns, provide insights that would narrow the gap between management's objectives and worker experiences. By addressing these challenges, we aspire to a future where businesses thrive, not just in terms of business profits but in nurturing empowered, valued teams.

1.4. Scope:

This research encompasses the in-depth analysis of a dataset of daily operational indicators of garment workers, including variables such as incentives, style changes, idle time, and work-in-progress. The information needs to be cleaned and pre-processed to make it accurate and reliable. In this regard, univariate and multivariate analyses will be carried out. Furthermore, this includes studying the correlations between the most relevant factors and productivity by applying non-parametric statistical methods because of the nature of the data. The derived insights would drive the management in the optimization of workflows, refinement of incentive structures, and reduction of production disruptions that could be applied across similar industries.

2. DESCRIPTIVE ANALYSIS:

The dataset provides a comprehensive view of garment factory productivity, comprising **1,197 observations** (rows) and **15 variables** (columns). Each row represents daily production data for a specific team, capturing a blend of operational and worker-centric metrics.

The dataset is a balanced mix of **10 numerical variables** and **5 categorical variables**. This diversity provides a rich foundation for exploring both quantitative trends and categorical group behaviours.

- **Categorical Variables**:
    - Variables like day and quarter can reveal temporal patterns (e.g., whether some days or weeks inherently more productive or not).
- **Numerical Variables**:
    - Metrics like actual_productivity and incentive are key to understanding the direct outcomes of operational strategies.
    - Variables like idle_time and wip help pinpoint inefficiencies in production processes.

Variable Descriptions	
date	Date in MM-DD-YYYY
day	Day of the Week
quarter	A portion of the month. A month was divided into four quarters
department	Associated department with the instance
team_no	Associated team number with the instance
no_of_workers	Number of workers in each team
no_of_style_change	Number of changes in the style of a particular product
targeted_productivity	Targeted productivity set by the Authority for each team for each day.
smv	Standard Minute Value, it is the allocated time for a task
wip	Work in progress. Includes the number of unfinished items for products
over_time	Represents the amount of overtime by each team in minutes
incentive	Represents the amount of financial incentive (in BDT) that enables or motivates a particular course of action.
idle_time	The amount of time when the production was interrupted due to several reasons
idle_men	The number of workers who were idle due to production interruption
actual_productivity	The actual % of productivity that was delivered by the workers. It ranges from 0-1.

```
PROC CONTENTS DATA=WORK.IMPORT; RUN;
```

```
proc means data=work.import;
run;
```

Alphabetic List of Variables and Attributes

#	Variable	Type	Len	Format	Informat
15	actual_productivity	Num	8	BEST12.	BEST32.
1	date	Num	8	MMDDYY10.	MMDDYY10.
4	day	Char	8	$8.	$8.
3	department	Char	9	$9.	$9.
12	idle_men	Num	8	BEST12.	BEST32.
11	idle_time	Num	8	BEST12.	BEST32.
10	incentive	Num	8	BEST12.	BEST32.
13	no_of_style_change	Num	8	BEST12.	BEST32.
14	no_of_workers	Num	8	BEST12.	BEST32.
9	over_time	Num	8	BEST12.	BEST32.
2	quarter	Char	8	$8.	$8.
7	smv	Num	8	BEST12.	BEST32.
6	targeted_productivity	Num	8	BEST12.	BEST32.
5	team	Num	8	BEST12.	BEST32.
8	wip	Num	8	BEST12.	BEST32.

The MEANS Procedure

Variable	N	Mean	Std Dev	Minimum	Maximum
team	1197	6.4269006	3.4639633	1.0000000	12.0000000
targeted_productivity	1197	0.7296324	0.0978910	0.0700000	0.8000000
standard_minute_value	1197	15.0621721	10.9432192	2.9000000	54.5600000
work_in_progress	691	1190.47	1837.46	7.0000000	23122.00
over_time	1197	4567.46	3348.82	0	25920.00
incentive	1197	38.2105263	160.1826428	0	3600.00
idle_time	1197	0.7301587	12.7097565	0	300.0000000
idle_men	1197	0.3692565	3.2689873	0	45.0000000
no_of_style_change	1197	0.1503759	0.4278479	0	2.0000000
no_of_workers	1197	34.6098580	22.1976867	2.0000000	89.0000000
actual_productivity	1197	0.7350911	0.1744879	0.2337055	1.1204375

The most critical variables in our case are actual_productivity and targeted_productivity as the measure the targeted performance and the actual performance of the workers.

Variables like incentive, no_of_style_change, and idle_time, can be significant predictors theoretically. We will later confirm the same numerically and factually using correlations during our EDA phase of the project.

3. DATA PREPROCESSING:

Data cleaning and preprocessing are critical steps in ensuring that the dataset is reliable and suitable for analysis. For this project, significant efforts were made to clean the data, address quality issues, and preprocess the variables to extract meaningful insights.

3.1. Renaming Ambiguous Variables for Clarity:

The dataset initially contained several variables with names that were either unclear or inconsistent. To improve interpretability and ease of analysis, ambiguous variable names were renamed to reflect their purpose more intuitively. For example:

- smv was retained as "Standard Minute Value" since it is a common term in the garment industry but clarified in documentation.
- Other columns like wip were explicitly documented to align with their meanings (e.g., "Work in Progress").

This step ensured that both the analysis process and any external review could quickly grasp the context of each variable.

```
/* Renaming the ambiguous variables */
DATA WORK.IMPORT;
    SET WORK.IMPORT;
    RENAME wip = work_in_progress;
    RENAME smv = standard_minute_value;
RUN;
```

3.2. Removal of Redundant Columns:

Certain variables, specifically date, was identified as redundant during the analysis. While date provided temporal information, other variables like day and quarter already captured essential temporal patterns. Dropping date reduced noise in the dataset and simplified analysis without compromising the richness of insights.

```
/* Dropping the redundant columns from the dataset */
DATA WORK.IMPORT;
    SET WORK.IMPORT;
    DROP date;
RUN;
```

3.3. Handling Missing Values:

Missing values in the wip (Work in Progress) variable posed a challenge, as ignoring them could have introduced bias or reduced the dataset's reliability. To address this, **Multiple Imputation (MI)** was used—a method that fills in missing values by creating multiple plausible datasets based on patterns in the data. Unlike simpler methods like mean imputation, MI preserves the variability and relationships between variables by modelling dependencies. For example, wip values were estimated using related variables like no_of_workers, actual_productivity, and idle_time, ensuring realistic and representative imputations.

MI was chosen because it retains the dataset's completeness without discarding valuable rows, effectively handling uncertainty by generating five different imputed datasets. This approach avoids overconfidence in results and captures the variability of missing data. After imputation, the datasets were combined into a single version for analysis, ensuring both reliability and readiness for advanced statistical methods like correlation analysis and modelling. By leveraging MI, the dataset's integrity was maintained, contributing to robust and actionable insights.

```
/* Checking the missing values for all our variables */
PROC MEANS DATA=WORK.IMPORT N NMISS;
RUN;
/* Only the variable wip has missing values (506) */

/* MI Imputation on the work_in_progress column */
PROC MI DATA=WORK.IMPORT nimpute=5 OUT=IMPUTED_DATA;
    VAR work_in_progress incentive; /* Predicting the missing values of work_in_progress with the help of incentive */
RUN;

/* Filter only the observations from the final imputation */
DATA FINAL_IMPUTATION;
    SET IMPUTED_DATA;
    WHERE _Imputation_ = 5; /* Keep only the 5th imputation */
RUN;

PROC MEANS DATA=FINAL_IMPUTATION N NMISS;
RUN;
/* As you can see the missing values are imputed */
```

The MEANS Procedure

Variable	N	N Miss
date	1197	0
team	1197	0
targeted_productivity	1197	0
smv	1197	0
wip	691	506
over_time	1197	0
incentive	1197	0
idle_time	1197	0
idle_men	1197	0
no_of_style_change	1197	0
no_of_workers	1197	0
actual_productivity	1197	0

The MEANS Procedure

Variable	Label	N	N Miss
Imputation	Imputation Number	1197	0
team		1197	0
targeted_productivity		1197	0
standard_minute_value		1197	0
work_in_progress		1197	0
over_time		1197	0
incentive		1197	0
idle_time		1197	0
idle_men		1197	0
no_of_style_change		1197	0
no_of_workers		1197	0
actual_productivity		1197	0

3.4. Outlier Detection and Treatment:

Outliers can distort statistical measures and introduce bias into the analysis. Using the **Interquartile Range (IQR)** method:

- Variables like actual_productivity, incentive, and idle_time were assessed for extreme values.
- Outliers were identified as values lying outside 1.5 times the IQR from the first or third quartile.
- These outliers were removed to enhance the reliability of statistical relationships without losing the core data's variability.

By addressing outliers, we ensured that the data better reflected typical production behaviours, leading to more accurate insights.

```
/* Calculate IQR and create a dataset with Q1 and Q3 */
PROC UNIVARIATE DATA=FINAL_IMPUTATION NOPRINT;
    VAR work_in_progress;
    OUTPUT OUT=IQR_wip Q1=Q1 Q3=Q3;
RUN;
/* Identify and Removal of Outliers Using IQR */
DATA FINAL_IMPUTATION;
    SET FINAL_IMPUTATION;
    /* Merge IQR values */
    IF _N_ = 1 THEN SET IQR_wip;
    IQR = Q3 - Q1;
    LOWER_BOUND = Q1 - 1.5 * IQR;
    UPPER_BOUND = Q3 + 1.5 * IQR;
    /* Remove Outliers */
    IF actual_productivity < LOWER_BOUND OR actual_productivity > UPPER_BOUND THEN
        DELETE;
RUN;
```

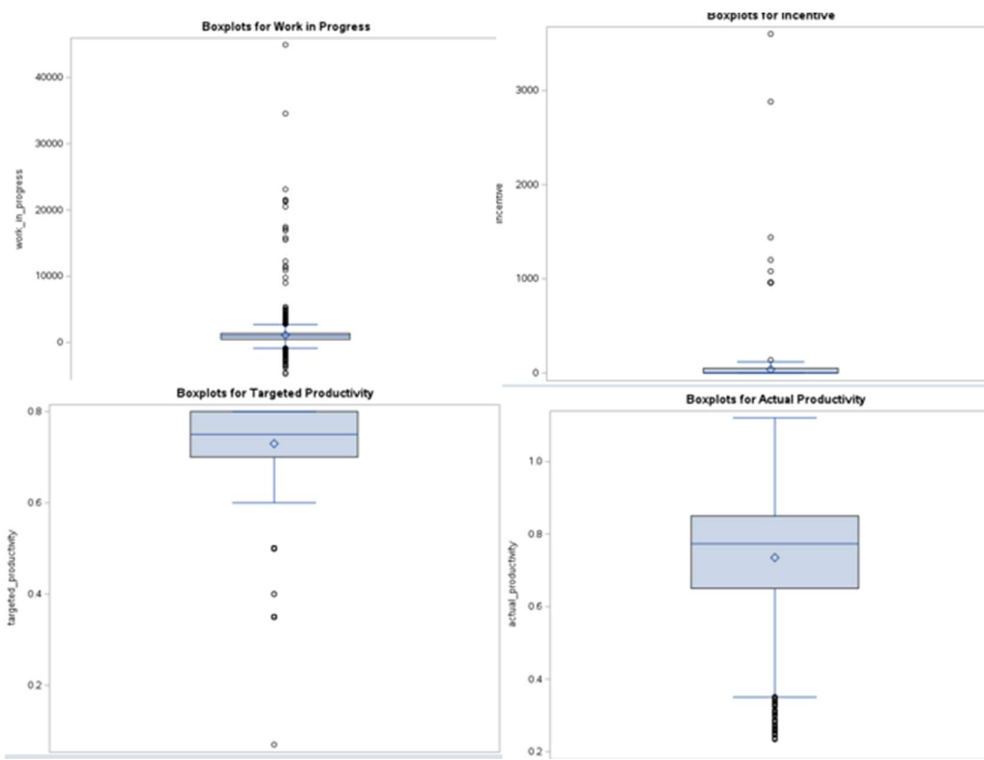
4. EXPLORATORY DATA ANALYSIS:

The exploratory data analysis (EDA) phase focused on uncovering patterns, relationships, and insights within the dataset to better understand the factors influencing garment worker productivity. A combination of univariate, bivariate, and multivariate analyses was performed, supported by visualizations and statistical techniques, to comprehensively explore the data.

4.1. Univariate Analysis:

Univariate Analysis involved examining the distribution of individual variables, such as actual_productivity, incentive, and idle_time. Boxplots and histograms were used to identify variability, skewness, and outliers in these variables. For instance, the distribution of actual_productivity revealed significant variability across teams, while outliers in incentive highlighted cases of unusually high financial rewards.

```
/* Boxplots of some of the variables */
proc sgplot data=FINAL_IMPUTATION;
    vbox work_in_progress;
    title "Boxplots for Work in Progress";
run;
proc sgplot data=FINAL_IMPUTATION;
    vbox incentive;
    title "Boxplots for Incentive";
run;
proc sgplot data=FINAL_IMPUTATION;
    vbox targeted_productivity / boxwidth=0.5;
    title "Boxplots for Targeted Productivity";
run;
proc sgplot data=FINAL_IMPUTATION;
    vbox actual_productivity / boxwidth=0.5;
    title "Boxplots for Actual Productivity";
run;
```



4.2. Bivariate Analysis:

Here, we explored relationships between two variables to identify potential correlations. Key comparisons included incentive vs. actual_productivity, where a scatterplot showed a weak positive trend, suggesting that incentives have a modest impact on productivity. Similarly, no_of_style_change vs. actual_productivity exhibited a moderate negative correlation, indicating that frequent style changes disrupt workflow efficiency. These analyses were supported by Spearman's Rank Correlation to account for the non-normal distribution of the data.

```
/* Checking correlations of work_in_progress with other features for imputation */
PROC CORR DATA=FINAL_IMPUTATION;
    /*VAR work_in_progress over_time incentive idle_time actual_productivity standard_minute_value;*/
RUN;
```

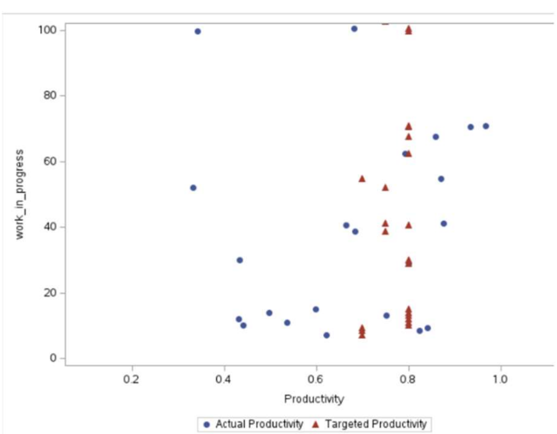
Pearson Correlation Coefficients
Prob > |r| under H0: Rho=0
Number of Observations

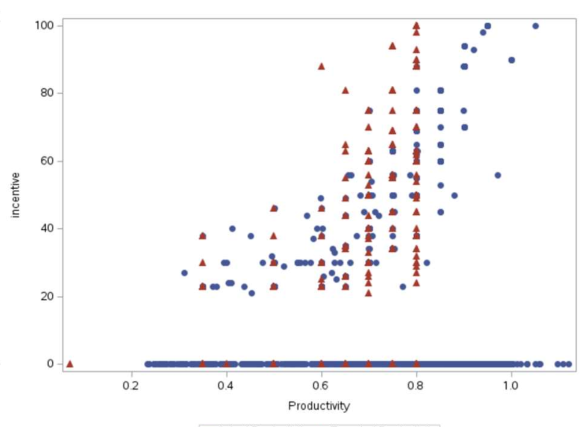
	date	team	targeted_productivity	standard_minute_value	work_in_progress	over_time	incentive	idle_time	idle_men	no_of_style_change	no_of_workers	actual_productivity
date	1.00000 1197	0.00886 0.7595 1197	-0.09896 0.0006 1197	0.00095 0.9737 1197	-0.03096 0.4164 691	-0.25459 <.0001 1197	0.10577 0.0002 1197	0.00782 0.7870 1197	0.07698 0.0077 1197	0.31506 <.0001 1197	-0.01222 0.6728 1197	-0.12257 <.0001 1197
team	0.00886 0.7595 1197	1.00000 1197	0.03027 0.2953 1197	-0.11001 0.0001 1197	-0.03347 0.3796 691	-0.09674 0.0008 1197	-0.00767 0.7908 1197	0.00380 0.8956 1197	0.02697 0.3511 1197	-0.01119 0.6988 1197	-0.07511 0.0093 1197	-0.14875 <.0001 1197
targeted_productivity	-0.09896 0.0006 1197	0.03027 0.2953 1197	1.00000 1197	-0.06949 0.0162 1197	0.06205 0.1031 691	-0.08856 0.0022 1197	0.03277 0.2573 1197	-0.05618 0.0520 1197	-0.05382 0.0627 1197	-0.20929 <.0001 1197	-0.08429 0.0035 1197	0.42159 <.0001 1197
standard_minute_value	0.00095 0.9737 1197	-0.11001 0.0001 1197	-0.06949 0.0162 1197	1.00000 1197	-0.03784 0.3206 691	0.67489 <.0001 1197	0.03263 0.2593 1197	0.05686 0.0492 1197	0.10590 0.0002 1197	0.31539 <.0001 1197	0.91218 <.0001 1197	-0.12209 <.0001 1197
work_in_progress	-0.03096 0.4164 691	-0.03347 0.3796 691	0.06205 0.1031 691	-0.03784 0.3206 691	1.00000 691	0.02230 0.5584 691	0.16721 <.0001 691	-0.02630 0.4901 691	-0.04872 0.2009 691	-0.07236 0.0573 691	0.03038 0.4252 691	0.13115 0.0005 691
over_time	-0.25459 <.0001 1197	-0.09674 0.0008 1197	-0.08856 0.0022 1197	0.67489 <.0001 1197	0.02230 0.5584 691	1.00000 1197	-0.00479 0.8684 1197	0.03104 0.2833 1197	-0.01791 0.5358 1197	0.05979 0.0386 1197	0.73416 <.0001 1197	-0.05421 0.0608 1197
incentive	0.10577 0.0002 1197	-0.00767 0.7908 1197	0.03277 0.2573 1197	0.03263 0.2593 1197	0.16721 <.0001 691	-0.00479 0.8684 1197	1.00000 1197	-0.01202 0.6777 1197	-0.02114 0.4650 1197	-0.02661 0.3577 1197	0.04922 0.0887 1197	0.07654 0.0081 1197
idle_time	0.00782 0.7870 1197	0.00380 0.8956 1197	-0.05618 0.0520 1197	0.05686 0.0492 1197	-0.02630 0.4901 691	0.03104 0.2833 1197	-0.01202 0.6777 1197	1.00000 1197	0.55915 <.0001 1197	-0.01160 0.6885 1197	0.05805 0.0446 1197	-0.08085 0.0051 1197
idle_men	0.07698 0.0077 1197	0.02697 0.3511 1197	-0.05382 0.0627 1197	0.10590 0.0002 1197	-0.04872 0.2009 691	-0.01791 0.5358 1197	-0.02114 0.4650 1197	0.55915 <.0001 1197	1.00000 1197	0.13363 <.0001 1197	0.10695 0.0002 1197	-0.18173 <.0001 1197
no_of_style_change	0.31506 <.0001 1197	-0.01119 0.6988 1197	-0.20929 <.0001 1197	0.31539 <.0001 1197	-0.07236 0.0573 691	0.05979 0.0386 1197	-0.02661 0.3577 1197	-0.01160 0.6885 1197	0.13363 <.0001 1197	1.00000 1197	0.32779 <.0001 1197	-0.20737 <.0001 1197
no_of_workers	-0.01222 0.6728 1197	-0.07511 0.0093 1197	-0.08429 0.0035 1197	0.91218 <.0001 1197	0.03038 0.4252 691	0.73416 <.0001 1197	0.04922 0.0887 1197	0.05805 0.0446 1197	0.10695 0.0002 1197	0.32779 <.0001 1197	1.00000 1197	-0.05799 0.0449 1197
actual_productivity	-0.12257 <.0001 1197	-0.14875 <.0001 1197	0.42159 <.0001 1197	-0.12209 <.0001 1197	0.13115 0.0005 691	-0.05421 0.0608 1197	0.07654 0.0081 1197	-0.08085 0.0051 1197	-0.18173 <.0001 1197	-0.20737 <.0001 1197	-0.05799 0.0449 1197	1.00000 1197

4.3. Multivariate Analysis:

Multivariate Analysis investigated the combined effects of multiple variables on productivity. For instance, we analyzed how work_in_progress (WIP) interacts with other variables like idle_time and over_time to influence actual_productivity. Clustered scatterplots helped visualize the interplay of these factors, revealing complex dependencies that single-variable analyses might overlook.

```
/* Scatterplots comparing actual_productivity and targeted_productivity with work_in_grogress and incentive */
PROC SGPLOT DATA=FINAL_IMPUTATION;
    YAXIS MIN=0 MAX=100 LABEL='work_in_progress';
    XAXIS LABEL='Productivity';
    SCATTER x=actual_productivity y=work_in_progress / MARKERATTRS=(SYMBOL=CIRCLEFILLED) LEGENDLABEL="Actual Productivity";
    SCATTER x=targeted_productivity y=work_in_progress / MARKERATTRS=(SYMBOL=TRIANGLEFILLED) LEGENDLABEL="Targeted Productivity";
RUN;
PROC SGPLOT DATA=FINAL_IMPUTATION;
    YAXIS MIN=0 MAX=100 LABEL='incentive';
    XAXIS LABEL='Productivity';
    SCATTER x=actual_productivity y=incentive / MARKERATTRS=(SYMBOL=CIRCLEFILLED) LEGENDLABEL="Actual Productivity";
    SCATTER x=targeted_productivity y=incentive / MARKERATTRS=(SYMBOL=TRIANGLEFILLED) LEGENDLABEL="Targeted Productivity";
RUN;
```





5. MODEL

5.1. Model Selection:

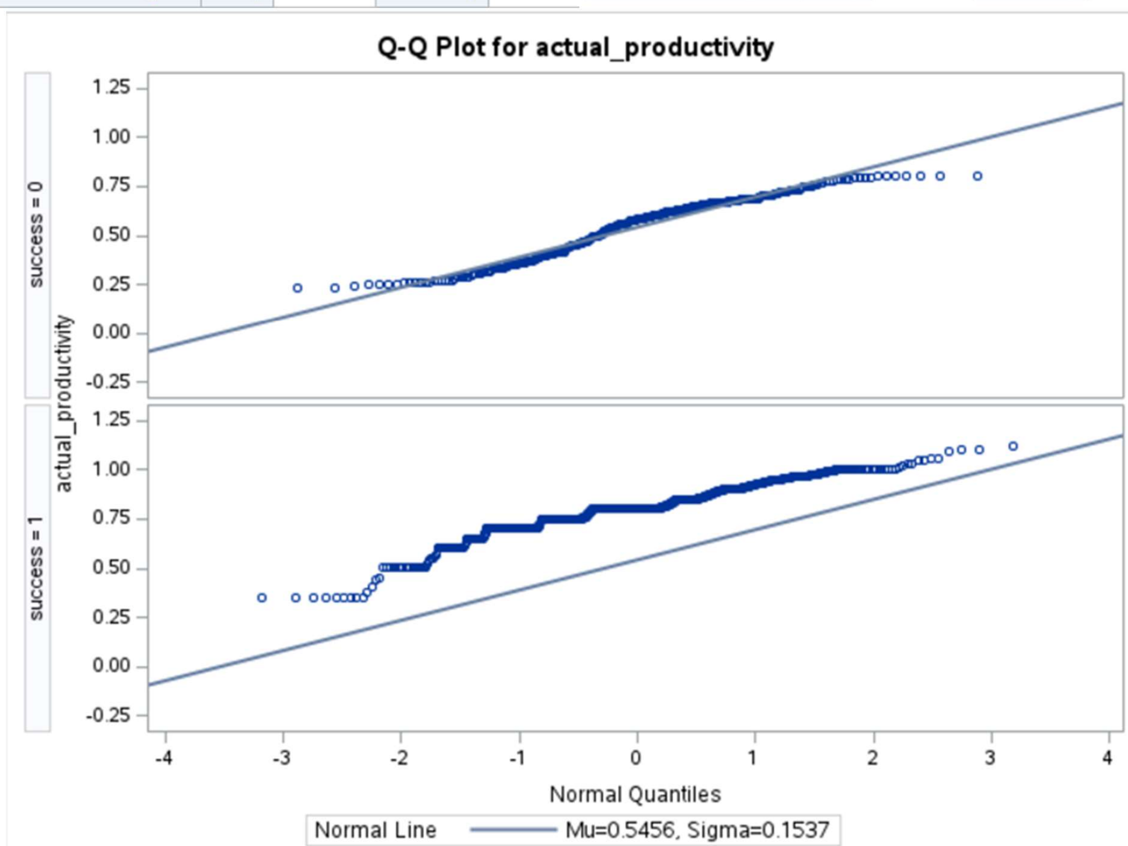
Non-parametric tests were chosen because the dataset violated key assumptions required for parametric tests, such as normality and homogeneity of variance. Tests like the Shapiro-Wilk and visual analyses (e.g., histograms) revealed that variables such as actual_productivity and incentive were skewed, with outliers and non-linear relationships. These issues rendered parametric methods unsuitable for this analysis.

```
/*
Basic Assumptions to decide on either parametric or non-parametric test
/*
Independence: As it is a real world dataset of worker productivity, we need to assume that one's productivity does not impact the other in any way
*/
/* Normality: Q-Q plot (or) Histogram */
PROC UNIVARIATE DATA=FINAL_IMPUTATION NORMAL;
    CLASS success;
    VAR actual_productivity;
    QQPLOT actual_productivity / NORMAL(MU=EST SIGMA=EST);
    TITLE "Q-Q Plot of actual productivity by success";
RUN;

/* As Normality is failing we can't do a parametric test and are opting for a non-parametric one */
```

Tests for Normality				
Test	**Statistic**		**p Value**	
Shapiro-Wilk	W	0.952129	Pr < W	<0.0001
Kolmogorov-Smirnov	D	0.109175	Pr > D	<0.0100
Cramer-von Mises	W-Sq	0.870092	Pr > W-Sq	<0.0050
Anderson-Darling	A-Sq	4.966665	Pr > A-Sq	<0.0050

Tests for Normality				
Test	**Statistic**		**p Value**	
Shapiro-Wilk	W	0.948803	Pr < W	<0.0001
Kolmogorov-Smirnov	D	0.13323	Pr > D	<0.0100
Cramer-von Mises	W-Sq	2.056106	Pr > W-Sq	<0.0050
Anderson-Darling	A-Sq	11.57672	Pr > A-Sq	<0.0050



Real-world datasets, like this one, rarely conform to ideal statistical assumptions due to inherent variability, production disruptions, and complex worker behaviours. Non-parametric tests, such as Spearman's Rank Correlation, are robust to outliers, do not require normal distributions, and effectively handle monotonic but non-linear relationships. This choice ensured accurate and meaningful insights, reflecting the dataset's real-world complexity while maintaining the integrity of the analysis.

5.2. Justification of Pearsons's Test:

5.2.1. Clear Interpretability:

The Pearson correlation coefficient provides a precise numerical value representing the strength of a linear relationship. For instance, a correlation value close to 0.2 suggests a weak but positive association, which can be directly linked to practical management strategies, such as adjusting incentive structures.

5.2.2. Actionable Insights for Decision-Making:

Pearson's test is particularly valuable for understanding direct, proportional changes between variables. For example, if financial incentives show even a weak positive correlation with productivity, management can consider enhancing incentive programs while exploring other influential factors.

5.2.3. Applicability to Continuous Data:

Since variables like actual_productivity, and incentive are continuous and measured on a scale, Pearson's test fits naturally with these data types.

5.2.4. Validation of Linear Trends:

While scatterplots visually suggested linear relationships, Pearson's correlation quantified this trend and determined its statistical significance. This allowed for a precise assessment of whether incentives effectively boost productivity or whether other variables, like style changes, have stronger effects.

5.3. Stating the Hypothesis for the Tests:

Incentives and Productivity:
Null Hypothesis: There is no monotonic relationship between incentive and productivity be it actual or targeted.
Alternate Hypothesis: There is a monotonic relationship between incentive and productivity be it actual or targeted.

Style Changes and Productivity:
Null Hypothesis: There is no monotonic relationship between the number of style changes and productivity be it actual or targeted.
Alternate Hypothesis: There is a monotonic relationship between number of style changes and productivity be it actual or targeted.

5.4. Results:

5.4.1. Incentives and Productivity: A Weak Positive Correlation

The analysis revealed a **weak positive correlation ($r=0.21706$)** between incentive and actual_productivity with the relationship being **statistically significant ($p<0.0001$)**, indicating that **financial rewards only slightly improve** worker output. Similarly, the correlation between **incentive and targeted_productivity (r=0.20175)** was also **weak** but **statistically significant. (p<0.0001)**. Here, as the p-value is <0.0001, we **reject the null hypothesis** that there is a no monotonic relationship.

- **Motivational Theory**: According to incentive-based motivation theories, financial rewards encourage workers to perform better, as they associate higher productivity with tangible benefits. However, in this context, the weak correlation suggests diminishing returns; after a certain point, additional incentives may fail to significantly motivate workers due to factors like physical fatigue or job dissatisfaction.
- **Operational Realities**: Workers in garment factories often operate within rigid workflows and physical constraints. Even with financial incentives, their productivity is limited by factors such as machine capacity, team coordination, and task complexity. Hence, the correlation is present but not strong.
- **Cultural and Social Factors**: In regions where garment factories are prevalent, workers may value job security over variable incentives, leading to a less pronounced response to financial rewards.

```
/*
Null Hypothesis: There is no monotonic relationship between incentive and actual or targeted productivity.
Alternate Hypothesis: There is a monotonic relationship between incentive and actual or targeted productivity.
*/
PROC CORR DATA=FINAL_IMPUTATION SPEARMAN;
    VAR incentive; /* Predictor variable */
    WITH actual_productivity targeted_productivity; /* Outcome variables */
    TITLE "Spearman's Rank Correlation between Incentive and Productivity";
RUN;
```

Spearman's Rank Correlation between Incentive and Productivity

The CORR Procedure

2 With Variables:	actual_productivity targeted_productivity
1 Variables:	incentive

Simple Statistics

Variable	N	Mean	Std Dev	Median	Minimum	Maximum
actual_productivity	1197	0.73509	0.17449	0.77333	0.23371	1.12044
targeted_productivity	1197	0.72963	0.09789	0.75000	0.07000	0.80000
incentive	1197	38.21053	160.18264	0	0	3600

Spearman Correlation Coefficients, N = 1197
Prob > \|r\| under H0: Rho=0

	incentive
actual_productivity	0.21706 <.0001
targeted_productivity	0.20175 <.0001

5.4.2. Style Changes and Productivity: A Moderate Negative Correlation

The analysis found a **moderate negative correlation** between the number of style changes and **actual_productivity (r=−0.26583)** and **targeted_productivity (r=−0.27680)** with both the relationships being **statistically significant (p<0.0001)**, indicating that **frequent style changes disrupt workflow** and reduce output. Here, as the p-value is <0.0001, we **reject the null hypothesis** that there is a no monotonic relationship.

- **Workflow Disruption**: Frequent style changes require adjustments in production processes, such as reconfiguring machines, training workers on new tasks, and adapting quality control measures. These interruptions reduce the time available for actual production, leading to a drop in productivity.
- **Learning Curve Effect**: Each new style necessitates a learning period during which workers familiarize themselves with the new design and processes. During this phase, productivity naturally declines as workers adapt to the changes.

- **Psychological Impact**: Continuous changes can demotivate workers, creating stress and reducing their efficiency. Consistency in work is often associated with smoother operations and higher morale, both of which are compromised with frequent style shifts.

```
/*
Null Hypothesis: There is no monotonic relationship between no_of_style_change and actual or targeted productivity.
Alternate Hypothesis: There is a monotonic relationship between no_of_style_change and actual or targeted productivity.
*/
PROC CORR DATA=FINAL_IMPUTATION SPEARMAN;
    VAR no_of_style_change; /* Predictor variable */
    WITH actual_productivity targeted_productivity; /* Outcome variables */
    TITLE "Spearman's Rank Correlation between Number of Style Change and Productivity";
RUN;
```

Spearman's Rank Correlation between Number of Style Change and Productivity

The CORR Procedure

2 With Variables:	actual_productivity targeted_productivity
1 Variables:	no_of_style_change

Simple Statistics

Variable	N	Mean	Std Dev	Median	Minimum	Maximum
actual_productivity	1197	0.73509	0.17449	0.77333	0.23371	1.12044
targeted_productivity	1197	0.72963	0.09789	0.75000	0.07000	0.80000
no_of_style_change	1197	0.15038	0.42785	0	0	2.00000

Spearman Correlation Coefficients, N = 1197
Prob > |r| under H0: Rho=0

	no_of_style_change
actual_productivity	-0.26583 <.0001
targeted_productivity	-0.27680 <.0001

6. CONCLUSION:

The analysis of garment factory productivity has revealed critical insights into the factors that influence worker performance. Financial incentives showed a weak but significant positive correlation with productivity, indicating their role as a motivator, albeit with diminishing returns. On the other hand, frequent style changes demonstrated a moderate negative impact, highlighting the disruptive nature of process reconfigurations on workflow efficiency. Additional factors, such as idle time and idle workers, further emphasized the importance of operational consistency. These findings underline that while monetary incentives can boost productivity to some extent, addressing systemic inefficiencies like workflow disruptions and process interruptions is key to achieving sustainable performance improvements.

7. RECOMMENDATIONS:

- **Optimize Incentive Structures**: Design incentive programs that reward team-based and long-term achievements rather than short-term individual output, ensuring motivation without overstretching physical limits.
- **Minimize Style Changes**: Streamline production planning to reduce frequent shifts in product styles. This could involve consolidating similar tasks or scheduling changes during less critical production periods.

- **Reduce Idle Time**: Implement robust workflow monitoring systems to identify and address the root causes of production interruptions, such as resource shortages or machine breakdowns.
- **Upskill Workers**: Provide training that equips workers to adapt quickly to style changes or other operational shifts, reducing the learning curve and minimizing disruptions.
- **Enhance Communication**: Foster better coordination between management and workers to ensure clarity in expectations and a smoother adaptation to operational changes.

8. REFERENCES:

- "Productivity Prediction of Garment Employees," UCI Machine Learning Repository, 2020. [Online]. Available: https://doi.org/10.24432/C51S6D