Efficiency of Full and Fractional Factorial Designs in Quality Management: A Case Study on Identifying Key Adhesion Factors

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Abstract

The Design of Experiments (DoE) method is a fundamental tool in quality management, providing a structured approach to process optimisation, reducing variability, and identifying key factors that influence outcomes. By systematically planning, executing, and analysing experiments, DoE enables quality management professionals to enhance product performance and consistency. The aim of this study is to compare the effectiveness of full factorial and fractional factorial experiment designs in quality management, specifically in identifying statistically significant factors that impact the adhesion properties of thermoplastic polyurethane (TPU) film with an acrylic-silicone adhesive, applied to laboratory glass with standardised parameters. The methodology comprises laboratory experiments designed to determine significant variables influencing adhesion, followed by statistical analysis using Minitab software. Both experiment types revealed the same primary factor as statistically significant. However, the fractional factorial design omitted additional significant factors due to data reduction, which led to some information loss. Despite this limitation, the fractional factorial design demonstrated high efficiency in terms of resource utilisation, including time and cost savings, while maintaining essential insights with minimal loss of valuable data. The findings contribute theoretically to the field of quality management, underscoring the comparative advantages and limitations of fractional factorial designs in scenarios where resources are constrained. Practically, this study provides guidance for quality management practitioners, indicating that while fractional factorial designs are cost-effective and time-efficient, they require meticulous data analysis to ensure the completeness and accuracy of findings, especially in complex experimental settings where missing critical information may impact decision-making.

Key words

design of experiments (DoE), fractional factorial experiment, full factorial experiment, quality management, process optimisation, adhesion properties, thermoplastic polyurethane (TPU)

Cite as:

Kwilinski, A., & Kardas, M., (2024). Business Investment Opportunities for Community Welfare: Evidence from Indonesia. *Forum Scientiae Oeconomia*, *12*(3), 138–155. https://doi.org/10.23762/FSO_VOL12_NO3_7

Received: 4 April 2023
Revised: 28 August 2024
Accepted: 7 September 2024

Introduction

Production processes and products generate substantial amounts of data, which reveal potential new optimisation opportunities within quality management. However, the abundance of coexisting factors often makes it challenging for process owners to detect key quality-related events. This difficulty arises from errors in data collection, data multiplicity, or misinterpretation. To accurately capture the cause-effect relationships within processes and identify statistically significant factors, it is essential to create conditions that support the identification of such critical events.

The Design of Experiments (DoE) methodology, as in other scientific disciplines, has its own terminology, methodology, and scope of study. The discipline's name itself indicates that it is focused on experimental methods (Lazić, 2004). DoE should be understood as a comprehensive statistical tool designed for managing and optimising process and product quality. This approach allows for the modelling and optimisation of processes by identifying statistically significant factors that have a substantial impact on quality management. The added value of experimental design lies in determining optimal parameter values, enabling a more intensive focus on quality within process or product management. Through the simultaneous manipulation of multiple input factors, DoE enables the study of their interactions, which might otherwise be overlooked if only one factor were manipulated at a time (One Factor at a Time – OFAT) (Tanco et al., 2008). This characteristic is particularly advantageous when more than one factor is suspected to influence the experimental outcome (Zohrevandi & Bashiri, 2014). In terms of experiment design, models are generally divided into two main groups: full factorial and fractional factorial experiments (Antony, 2014; Kechagias et al., 2017). A full factorial experiment tests all relevant factor combinations at selected levels, while a fractional factorial experiment evaluates only a subset of combinations, potentially omitting higher-order interactions (McBurney & White, 2007). The fractional factorial model is primarily used when resources, such as time or budget, are limited, which often leads to the full factorial model being overlooked or rarely implemented (Mønness et al., 2007).

The number of runs in a full factorial experiment can be significant and grows exponentially. For example, an experiment with seven variable factors requires 128 runs (Zhu, 2005). The fractional factorial model allows a substantial reduction in the number of runs, although it generates an alias structure, where factors may interact with higher-order terms, complicating the interpretation of results. This complexity underscores the importance of thorough analysis to distinguish between the influence of a primary factor and the effect of interactions when assessing the sources of variability (Minitab 21 Support; Yang & Draper, 2003).

1. Literature review

The issue of quality has long attracted the attention of researchers striving to understand and optimise production processes (Anguo, 2004; Shammot, 2011). Quality can be defined as a set of characteristics enabling a product or service to meet user needs and stand out among competitors (Saxena & Srinivas Rao, 2019). It encompasses not only the product itself but also the entire process of its creation, requiring the involvement of all participants. In a philosophical context, particularly within the framework of Hegel's laws of dialectics, quality is interconnected with the category of quantity. In practice, this means that changes in quantitative metrics within the production process can influence product quality. For example, an increase in production volume without consideration for resources and control may lead to a decline in quality. Consequently, quality management serves as a key tool for maintaining balance between the quantitative and qualitative characteristics of products.

Recent research also pays considerable attention to various aspects of quality management in the context of sustainable development, digitalisation, and entrepreneurship. Quality management is explored from the perspective of sustainable development, emphasising the importance of maintaining balance across economic, environmental, and social factors (Acheampong et al., 2023; Chen et al., 2024; Kwilinski & Trushkina, 2023; Kwilinski & Kardas, 2023, 2024; Kwilinski et al., 2023a, 2023b, 2024b, 2024d; Lyulyov et al., 2024a, 2024b; Mlaabdal et al., 2024). In the context of digitalisation, quality management extends to virtual spaces and digital processes, which are increasingly pivotal in modern production (Acheampong et al., 2023; Ayala-Mora et al., 2023; Climent et al., 2024; Eisinger Balassa et al., 2024; Furelid Tellnes et al., 2024; Infante-Moro et al., 2022a, 2022b, 2023; Kamińska-Witkowska & Kaźmierczak, 2024; Khan et al., 2022; Kwilinski, 2019, 2024; Kwilinski et al., 2023c, 2024a, 2024c, 2024d; Lis, 2021; Lugito et al., 2024; Lyulyov et al., 2024a, 2024c; Maheshwari, 2024; Nguyen et al., 2024; Strielkowski et al., 2024; Wahyundaru et al., 2024; Wu et al., 2024). Meanwhile, entrepreneurship is investigated in the context of system sustainability from the perspective of business adaptability and the adoption of innovative approaches to quality maintenance (Anguo et al., 2004; Baldi, 2020; Batz Liñeiro et al., 2024; Chygryn et al., 2024; Dacko-Pikiewicz, 2019a, 2019b; Erden Ayhun et al., 2024; Khalid & Kot, 2021; Lei et al., 2024; Nadason et al., 2024; Rajiani & Kot, 2020; Szczepańska-Woszczyna, 2018; Szczepańska-Woszczyna & Gatnar, 2022; Shikhli et al., 2024; Solórzano Solórzano et al., 2024; Szczepańska-Woszczyna & Muras, 2023; Wróblewski & Dacko-Pikiewicz, 2018; Wolniak et al., 2024; Wróblewski et al., 2017; Zane & Zimbroff, 2018; Zatar, 2022; Zimbroff, 2023; Zimbroff & Jorgensen, 2019; Zimbroff et al., 2017, 2021). These research areas highlight the relevance of an interdisciplinary approach to quality management for maintaining stability and optimising processes at all levels.

Modern approaches to quality management focus not only on the final stages of product release but also on all phases of the production process, including design, development, testing, and implementation (Bucko et al., 2022). This comprehensive focus is essential for both small manufacturing firms and large-scale operations, as product quality and process efficiency require continuous monitoring and adaptation to evolving conditions.

The Design of Experiments (DoE) method is a statistical tool in quality management that enables the quantitative assessment of factor effects and interactions to optimise process parameters (Alagumurthi et al., 2006; Freiesleben et al., 2020; Jadhav & Sawant, 2024; Lee et al., 2022). In various industries, such as pharmaceuticals (Fukuda et al., 2018; Politis et al., 2017), chemistry (Murray et al., 2016; Heidari-Rarani et al., 2022), and medicine (Dong et al., 2008; Buang et al., 2014; Freitas et al., 2021), DoE supports the development of models aimed at quality improvement. Quality management across all phases—from design to testing and implementation—requires reliable data analysis tools, such as Minitab and Design Expert, which provide high levels of predictive accuracy (Ermergen & Taylan, 2024; Kwashabawa, 2021).

Based on the literature review, authors like Zohrevandi and Bashiri (2014), Kechagias et al. (2017), and Jankowski et al. (2016) emphasise the advantages of fractional factorial designs over full factorial designs. Both approaches yield similar results; however, fractional factorial designs are more resource-efficient, reducing time and cost, which is particularly valuable for large-scale processes.

While the Design of Experiments (DoE) method is a fundamental tool in quality management, providing a structured approach to process optimisation and variability reduction, several gaps persist in current research. Firstly, there is limited examination of the comparative effectiveness of full factorial and fractional factorial experiment designs in identifying statistically significant factors within quality management. Secondly, research is lacking on the potential loss of information inherent in fractional factorial designs, especially in cases where analytical precision is critically important. Additionally, there is a shortage of studies focused on the application of DoE for assessing the adhesion properties of specialised materials, such as thermoplastic polyurethane (TPU), with various adhesive types.

The aim of this study is to conduct a comparative analysis of the effectiveness of full and fractional factorial experiment designs in quality management, with a particular emphasis on identifying statistically significant factors that influence the adhesion properties of TPU film with an acrylic-silicone adhesive, applied to laboratory glass under standardised parameters.

The article is structured as follows: The introduction provides the theoretical foundation and significance of the Design of Experiments (DoE) method in quality management. Section 1 explores the core concepts and advantages of DoE, including definitions of full factorial and fractional factorial experiments. Section 2 details the research methodology, comprising laboratory experiments and statistical analysis conducted using Minitab software. Section 3 presents the results in the form of a comparative analysis between full and fractional factorial experiments, highlighting the differences and unique aspects of each approach. The discussion in Section 4 analyses the findings and discusses their implications for quality management, indicating the effectiveness and limitations of the two experimental methods. Finally, the conclusion summarises the key findings and offers practical recommendations for implementing DoE methods in resource-constrained environments.

2. Methodology

The research, conducted to identify the differences resulting from full factorial and fractional experimentation, adopts a quantitative research strategy. Data analysis was performed using Minitab 21.4.1, a statistical software package with a collection of programs designed to execute analyses with high numerical accuracy. This software utilises Automated Machine Learning tailored for both binary and continuous responses, drawing on capabilities from the Predictive Analytics Module. Specifically crafted to enhance business operations, Minitab offers user-friendly options for entering and manipulating statistical data, recognising patterns, and conducting thorough analyses to address practical business issues. It simplifies data analysis processes, making it well-suited for statistical evaluations at the business level. Minitab also includes visual tools, such as histograms, boxplots, and scatterplots, which assist professionals in performing statistical analyses more effectively and deriving insights from their data. Additionally, it enables users to compute descriptive statistics for their datasets. Today, Minitab is widely recognised as a prominent commercial application used in Lean Six Sigma projects (Alagić, 2021).

In alignment with the study's objective of highlighting differences between the two experimental models, the laboratory research focused on a case study measuring the adhesion strength of thermoplastic polyurethane (TPU) film coated with a hybrid adhesive (acrylic-silicone) applied to laboratory glass under standardised conditions. Four variable factors—material batch, glass preparation, application time, and curing time—were tested at two levels (-1 and +1), generating 16 independent runs (2^4) for the full factorial experiment. For the fractional factorial model, the number of runs was reduced to 8 (2^(4-1)).

The limitations of the study include measurements performed by a single laboratory technician, the use of one batch of laboratory flat glass (100 x 50 x 4 mm), ambient conditions controlled at 22.3°C ± 0.1 with 67% ± 1 humidity, and the fact that adhesion force measurements were performed using an Axis force meter, model FB, on an automatic tripod, model STAH. Additionally, TPU film samples were cut into strips of 15 cm length and 2.5 cm width and adhered to the glass surface using a generated test matrix that accounted for the individual levels of variable factors. The prepared test specimens were mounted on the instrument's tripod and then attached to the actuator's automatic gantry gripper. The speed of the automatic gantry was kept constant at -20 mm/s for each run.

3. Research results

The Results section is organised into three key areas. Section 3.1 provides a detailed analysis of the data generated by the full factorial experiment, whereas Section 3.2 examines the relationships identified within the fractional factorial experiment. Finally, Section 3.3 characterises the differences between the two approaches, with specific reference to the presented case study.

3.1. Full factorial experiment

The premise of the full factorial experiment was to comprehensively reveal all interactions and main effects resulting from the manipulation of variable factors at two levels. The batch of material, method of application, substrate preparation, and measurement time were identified as independent variables (Table 1). Expert knowledge of polymeric materials allowed the conclusion that the method of assembly, specifically the use of gel, could have a decisive influence on the activation of the acrylic-silicone adhesive. Other levels of the independent variable factors were selected based on process observation and quality issues identified within the application area.

Table 1. Levels of independent experiment variables.

Variable Factor	level (-1)	level (+1)
A: batch	1	2
B: application	without gel	gel
C: surface preparation	without preparation	surface degreasing
D: measurement after x	12h	24h

Source: own elaboration.

The full factorial experiment, targeting four variable factors tested at two levels, generated 16 independent runs (2^4). The complete test matrix and the resulting adhesion strength measurements for the full factorial model are presented in Table 2. It should be emphasised that the full factorial experiment does not account for the aliasing phenomenon, which can potentially lead to distortions and, ultimately, to the misinterpretation of statistically significant factors or interactions.

Table 2. Test matrix with results of the full factorial experiment.

Run Order	A	B	C	D	N	Run Order	A	B	C	D	N
1	-1	-1	-1	-1	7.0	9	1	1	-1	-1	23.5
2	-1	1	1	1	19.0	10	1	-1	-1	1	19.3
3	-1	-1	1	1	13.5	11	1	1	1	1	23.8
4	-1	1	-1	1	11.3	12	1	-1	1	-1	22.5
5	-1	-1	-1	1	8.4	13	1	-1	1	1	22.0
6	-1	1	-1	-1	8.5	14	1	1	-1	1	23.6
7	-1	-1	1	-1	12.0	15	1	-1	-1	-1	11.0
8	-1	1	1	-1	13.0	16	1	1	1	-1	23.5

Note: A – batch; B – application; C – surface preparation; D – measurement after x; N – result.
Source: own elaboration.

A statistical analysis of the variable factors, selected as potentially relevant based on expertise and process knowledge, revealed values for all possible main effects and interactions at the levels shown in Table 3. Statistical modelling of the obtained results was conducted using Minitab 21.4.1.

Table 3. Values of main effects and interactions; full factorial experiment.

Variable Factor	Effect	Coef
Constant		16.37
A: batch	9.563	4.781
B: application	3.813	1.906
C: surface preparation	4.588	2.294
D: measurement after x	2.488	1.244
A: batch*B: application	1.088	0.543
A: batch*C: surface preparation	-0.987	-0.494
A: batch*D: measurement after x	-0.437	-0.219
B: application*C: surface preparation	-1.488	-0.744
B: application*D: measurement after x	-0.187	-0.094
C: surface preparation*D: measurement after x	-0.663	-0.331
A: batch*B: application*C: surface preparation	-2.013	-1.001
A: batch*B: application* D: measurement after x	-1.663	-0.831
A: batch* C: surface preparation* D: measurement after x	-1.488	-0.744
B: application *C: surface preparation*D: measurement after x	1.513	0.756
A: batch* B: application*C: surface preparation*D: measurement after x	0.738	0.369

Source: own elaboration.

The data presented in Table 3 identify the batch variable factor as the most influential main effect, with its observed effect size nearly double that of the next most significant factor—surface preparation. To clearly identify which factors are statistically significant in this study, the data are displayed in a Pareto Chart (Figure 1) and a Normal Probability Plot (NPP, Figure 2). While both charts highlight individual effect sizes, the NPP also indicates the direction of each effect, whereas the Pareto Chart displays only absolute values.

Applying the Pareto principle, an α level of 20% was selected as the threshold for the probability of a false alarm. The α coefficient, alongside the experimental effect sizes, establishes a "water line" on the charts. All main effects and interaction effects falling below this line are considered statistically insignificant.

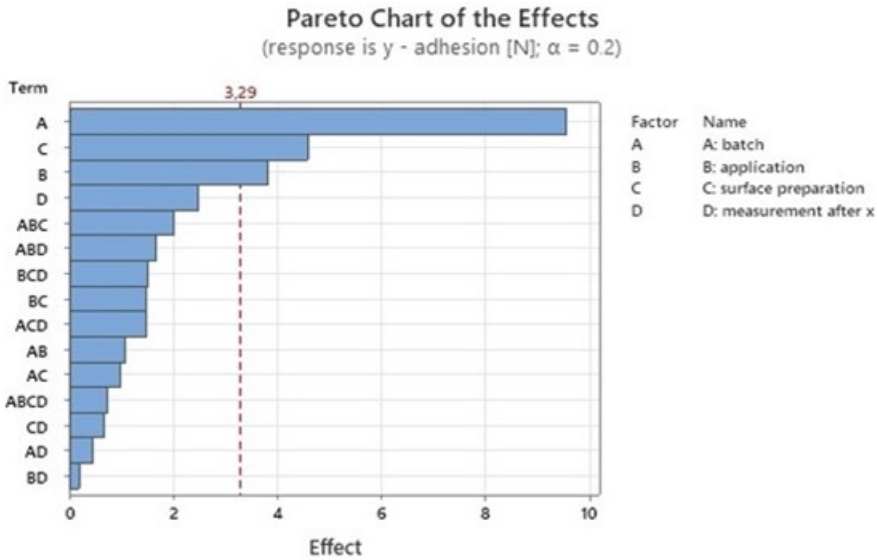

Figure 1. Pareto chart with relevance of factors of the full factorial experiment.
Source: own elaboration.

The data presented in Figure 1 correspond with the values in Table 3. Notably, in addition to the primary effect of the material batch, there are additional effects above the significance threshold, specifically for surface preparation and application. Figure 1 clearly indicates that factor D is not a critically influential parameter in contributing to variability within the experiment and, by extension, within the overall process. Furthermore, it should be highlighted that none of the interaction effects reach statistical significance.

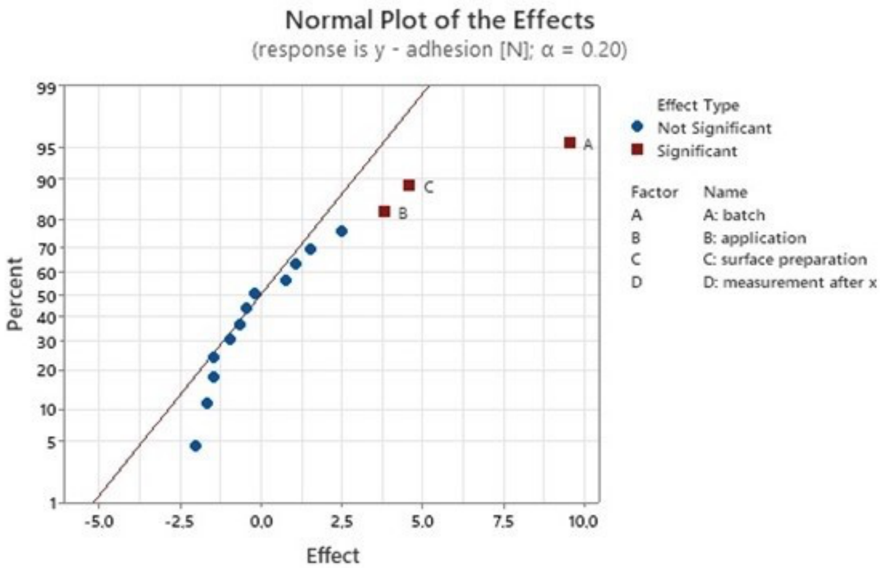

Figure 2. Normal Probability Plot – full factorial experiment.
Source: own elaboration.

Based on the experiment conducted and the calculated values of statistically significant factor effects, main effect charts were prepared, as shown in Figure 3. Referring to the conclusions of the case study, it is essential to highlight the absence of interaction between the factors, a finding that is primarily supported by Figure 1, where interactions are shown to be statistically insignificant.

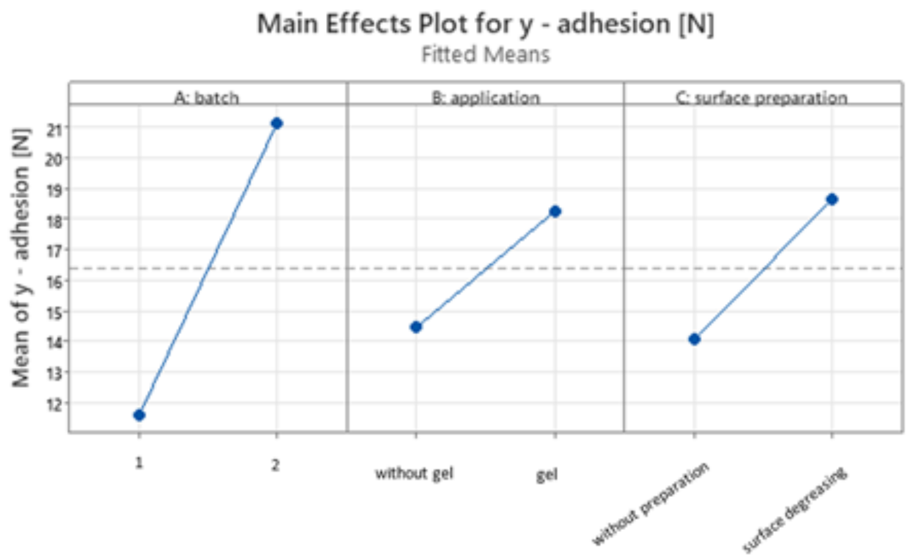

Figure 3. Graphs of the effects of the main factors A, B and C – full factorial experiment.
Source: own elaboration.

In interpreting the graph above—Figure 3—it is clear that changing the level of factor A, "batch," from (-1) to (+1) (i.e., from batch 1 to batch 2) leads to an average increase in adhesion, rising from 11.59 to 21.15 N. For the second factor, B, "applique," shifting the level from (-1) (no gel) to (+1) (assembly with gel) results in an average adhesion increase from 14.46 to 18.28 N. Similarly, for factor C, "surface preparation," changing from level (-1) (mounting the film without prior surface preparation and degreasing) to (+1) yields an average increase in adhesion strength from 14.08 to 18.66 N.

3.2. Fractional experiment

Similar to the full-factorial experiment, the fractional experiment involved testing four variable factors at the predetermined levels outlined in Table 1. Although the same factors were tested, the fractional experiment produced only 8 runs (2^(4-1)). The study's assumptions were identical to those of the full factorial experiment model.

To ensure full reproducibility and maintain a focus on comparing the two experimental models, the same data were applied for each individual run in the fractional experiment as in the full factorial experiment. The test matrix and the adhesion force results obtained from the fractional experiment are presented in Table 4.

Table 4. Test matrix with results of the fractional experiment.

Run Order	A	B	C	D	N	Run Order	A	B	C	D	N
1	-1	-1	-1	-1	7.0	5	1	1	-1	-1	23.5
2	-1	1	-1	1	11.3	6	1	1	1	1	23.8
3	-1	1	1	-1	13.0	7	1	-1	-1	1	19.3
4	-1	-1	1	1	13.5	8	1	-1	1	-1	22.5

Note: A – batch; B – application; C – surface preparation; D – measurement after x; N – result.
Source: own elaboration.

In the fractional experiment conducted, it is essential to note the presence of aliasing, which means that in this fourth-order resolution analysis, the main factor is confounded with third-order interactions (A=BCD). Additionally, second-order interactions are confounded with other interactions of the same order (AB=CD).

Statistical analysis of the variable factors, using the fractional experiment test matrix, revealed main effect values and interactions at the levels detailed in Table 5.

Table 5. Values of main effects and interactions; fractional experiment.

Variable Factor	Effect	Coef.
Constant		16.74
A: batch	11.075	5.538
B: application	2.325	1.163
C: surface preparation	2.925	1.463
D: measurement after x	0.475	0.238
A: batch*B: application	0.425	0.213
A: batch*C: surface preparation	-1.175	-0.588
A: batch*D: measurement after x	-1.925	-0.963

Source: own elaboration.

The data in Table 5 indicate that the strongest main effect remains the variable factor A: batch of material, as observed in the full-factorial experiment. The effect value for this factor is nearly four times that of the second factor, C: surface preparation. Importantly, due to the fractional model of the experiment, the main factor A is confounded with the third-order interaction BCD. Given that none of the individual factors forming this interaction are statistically significant, and that the interaction itself does not exhibit strong statistical significance overall, the confounding effect can be considered negligible.

In addition to the values presented in Table 5, the data are visualised in a Pareto chart (Figure 4) and a Normal Probability Plot (Figure 5). Following the Pareto principle, a significance level of 20 per cent was set as the value of α (probability of false alarm).

The data shown in Figure 4 correspond to the values presented in Table 5. It should be noted that, for the fractional experiment, only the variable factor A: batch of material, was identified as statistically significant.

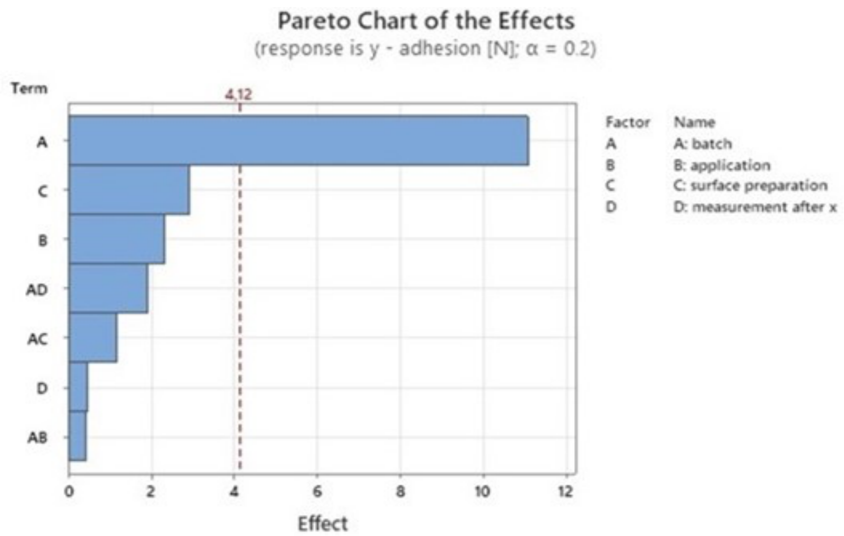

Figure 4. Pareto chart with relevance of factors of the fractional experiment.
Source: own elaboration.

These observations are further confirmed in Figure 5.

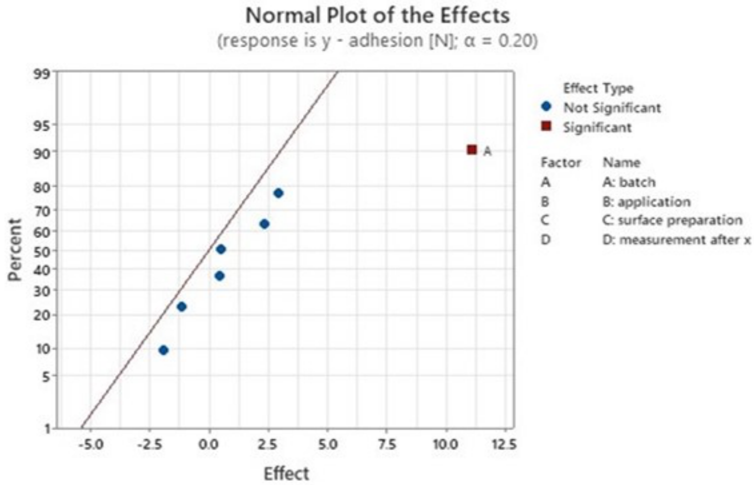

Figure 5. Normal Probability Plot – fractional experiment.
Source: own elaboration.

Based on the fractional experiment conducted and the results obtained, a main effects plot for factor A: material batch was generated, as shown in Figure 6.

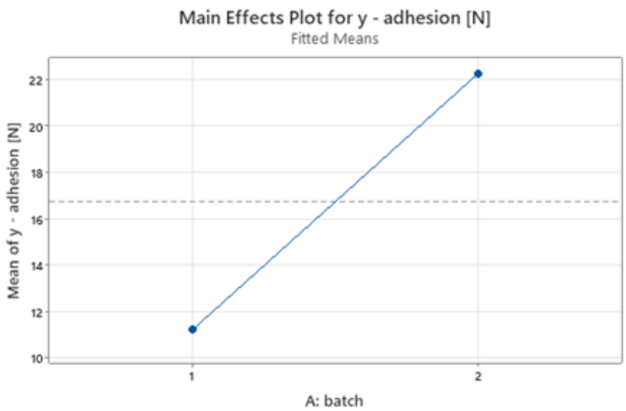

Figure 6. Graphs of the effect of the main factor A – fractional experiment.
Source: own elaboration.

Figure 6 demonstrates that for the main effect A: batch of material, shifting the level from (-1) for batch 1 to (+1) for batch 2 results in an increase in the mean adhesion strength from 11.2 N to 22.28 N.

3.3. Comparative analysis of the full factorial and fractionated experiment

The comparative analysis conducted between the full factorial and fractional experiments revealed some differences in identifying statistically significant factors that critically influence process variability. The full factorial experiment offers higher precision and a more standardised approach, as it includes all possible factor combinations. In contrast, the fractional experiment requires more sophisticated statistical analysis due to its limited number of combinations, which introduces the aliasing phenomenon. Notably, the higher the resolution level, the more robust a given factor or interaction appears within the aliasing structure.

Reviewing the effect values obtained from both experimental models highlights that, unlike the fractional experiment, the full factorial model identifies factors beyond A: material batch—specifically, B: application and C: surface preparation—as statistically significant (as shown in Tables 3 and 5). This disparity may lead to less precise control of the process when relying solely on fractional data, which identifies only the material batch factor as significant.

To undertake optimisation for the presented case study, it is essential first to standardise adhesion values across the individual material batches, particularly focusing on factor A.

4. Discussion

This study provides an in-depth comparative analysis of full and fractional factorial designs, specifically highlighting the differences in their utility, precision, and application suitability in quality management. A prominent takeaway from this research is the nuanced trade-off between the depth of insights afforded by the full factorial design and the efficiency provided by the fractional factorial approach. Full factorial designs offer a robust and detailed analysis, as each factor and interaction can be examined in isolation, eliminating confounding effects due to aliasing. This clarity is critical in fields where understanding the exact impact of each variable on outcomes is essential, particularly in quality-sensitive industries like pharmaceuticals or advanced materials (Politis et al., 2017; Fukuda et al., 2018). The results of this study underscore the full factorial design's capacity to provide a more granular understanding of factor interactions, a requirement in cases where subtle variations in process parameters may influence product efficacy or safety.

However, as Mønness et al. (2006) point out, the practicality of full factorial experiments is often constrained by resource limitations, as the approach can demand a substantial number of experimental runs, especially with an increasing number of factors. In contrast, fractional factorial designs, while inherently simpler, face limitations due to the aliasing of interactions. The results presented in this study demonstrate how the fractional design, despite its efficiency, omitted some interactions and secondary factors that the full factorial design was able to identify. These findings corroborate Mønness et al.'s (2006) suggestion that while fractional factorial experiments provide an effective initial screening tool, they may require supplementary experimentation to achieve the accuracy necessary for critical applications. This aligns with recommendations by Marrubini et al. (2020), who advocate for the use of fractional designs primarily for screening purposes, especially when the number of factors exceeds manageable levels for full factorial analysis.

This study also highlights the unique role of expertise in experimental design selection. Given the dependency of fractional factorial designs on assumptions about factor significance, domain knowledge becomes essential in guiding the design and interpreting its results effectively. Knowledge of material properties, process conditions, and expected factor interactions can inform decisions on which interactions to alias, thereby maximising the relevance of findings even within the constraints of fractional factorial designs. As demonstrated, the expertise in this study allowed for the prioritisation of main factors over less impactful interactions, thus aligning with strategic goals without sacrificing critical data.

In terms of practical implications, this research reinforces the idea that full factorial designs are ideal for applications requiring high precision and comprehensive factor analysis, whereas fractional factorial designs serve as a valuable cost-effective alternative in resource-limited environments. Quality management teams can utilise the findings of this study to determine the optimal experimental approach based on their specific process requirements, balancing the need for detailed insights against resource availability. Importantly, fractional factorial designs can be augmented with complementary analytical techniques or follow-up experiments to validate the primary findings, as suggested by this study's results on TPU adhesion properties.

Overall, this study contributes valuable insights to the discourse on experimental design in quality management, confirming that while both full and fractional factorial designs have distinct benefits, their selection must be strategically aligned with process demands, resource constraints, and desired outcome accuracy.

The limitations of this study primarily relate to the specific conditions and materials utilised, which may impact the generalisability of the findings. The experiments were conducted with a single batch of TPU material and under controlled laboratory conditions, including a constant temperature and humidity level, which do not fully reflect the variability encountered in real-world production environments. Additionally, the study employed a limited number of variable factors, focusing on four primary factors at two levels each. Expanding the number of factors or levels could yield further insights but would likely necessitate a higher number of runs, impacting resource demands.

Furthermore, the reliance on fractional factorial design introduces aliasing, which may obscure the significance of certain interactions in more complex processes. Future research could address these limitations by testing a broader range of materials, environmental conditions, and variable factors to enhance the applicability of the findings across diverse industrial contexts.

Conclusions

The interpretation of this study's results highlights the complex interplay between quality (K) and quantity (Q), a relationship rooted in philosophical principles such as Hegel's dialectics, where quantitative changes can lead to qualitative shifts. In the context of the experimental design, both full factorial and fractional factorial models underscore this connection, as manipulating quantitative aspects, such as the number of runs or the levels of factors, directly impacts the quality of the insights obtained. The full factorial approach, by accounting for all possible interactions, exemplifies how a comprehensive examination of quantity leads to a qualitatively richer understanding of the factors influencing TPU film adhesion. Meanwhile, the fractional factorial design, though less exhaustive, showcases that even a reduced quantitative approach can yield significant insights when guided by well-chosen factors, reflecting a strategic balance between K and Q. This dual approach, therefore, illustrates how quantitative and qualitative aspects of quality management can be aligned to maximise efficiency and depth within practical limitations.

The Pareto principle further enhances the interpretation of these findings, suggesting that only a select few factors in a quality management process may account for the majority of the outcomes. This principle aligns with both full and fractional factorial designs, where focusing on the most impactful factors—like material batch and surface preparation—enables a high return on quality insights with fewer resources. The Pareto approach thus reinforces the balance between quantity and quality, as it allows quality managers to concentrate on critical factors, ensuring effective quality improvements while conserving resources. In practice, adopting this rule can streamline the experimentation process, targeting only those factors with the greatest influence on outcomes, which is particularly beneficial in resource-constrained environments.

From a sustainable development perspective, the findings contribute to the broader discourse on responsible resource utilisation and efficient process optimisation. The fractional factorial experiment offers a compelling case for resource efficiency, aligning with sustainable development goals by minimising the consumption of time, materials, and energy while still providing valuable data for decision-making. Such efficiency is especially relevant in the modern industrial context, where sustainability considerations demand approaches that balance thorough analysis with resource-conscious practices. This study supports the notion that fractional factorial designs, when employed judiciously, can serve as an effective tool in sustainable quality management, where the essential trade-off between depth and resource conservation must be carefully managed.

The integration of advanced data-processing tools like Minitab into quality management practices further emphasises the evolving role of technology in handling large and complex datasets. Automated Machine Learning (AutoML) and predictive analytics modules within such software enable quality professionals to analyse vast amounts of data with enhanced accuracy and speed, bridging the gap between traditional statistical analysis and modern big data approaches. The ability to process and visualise data with tools such as Pareto charts, normal probability plots, and main effect charts exemplifies how new technologies empower organisations to interpret complex data structures more effectively. This capability is critical in today's data-rich environments, allowing companies to refine quality management strategies and extract insights that might otherwise remain obscured in extensive datasets.

To advance these insights, further studies could explore how big data analytics can enhance factorial experiment designs, especially in managing and interpreting large-scale industrial data with real-time adjustments for quality management. Investigating how fractional factorial models perform under machine learning-based optimisation could provide an innovative framework that extends the traditional DoE approach into the realm of adaptive quality management. Additionally, future research could delve into the application of the Pareto principle in dynamic quality environments, exploring adaptive models that identify and prioritise key factors as conditions fluctuate. Such research would serve to better align the theoretical underpinnings of quality and quantity relationships with practical applications in sustainable development and big data-driven environments.

Author Contributions: Conceptualization, A.K. and M.K.; methodology, A.K. and M.K.; software, A.K. and M.K.; validation, A.K. and M.K.; formal analysis, A.K. and M.K.; investigation, A.K. and M.K.; resources, A.K. and M.K.; data curation, A.K. and M.K.; writing-original draft preparation, A.K. and M.K.; writing-review and editing, A.K. and M.K.; visualization, A.K. and M.K. Each author has contributed equally to this work. All authors have read and agreed to the published version of the manuscript.

Funding: This study did not receive any financial support.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgements: The authors express their heartfelt gratitude to the reviewers and editorial board for their invaluable feedback, thoughtful insights, and constructive guidance, all of which significantly enhanced this manuscript. Their meticulous review and dedication played a crucial role in refining our work, and we are sincerely grateful for their commitment and professionalism throughout the review process.

Conflicts of Interest: The authors declare that there are no conflicts of interest regarding this study.

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