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Article

Optimizing processes and products: The role of DOE

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Abstract: The Design of Experiment (DOE) methodology is a fundamental tool for systematic inquiry and optimization in both scientific and industrial applications. The DOE's statistical framework is designed to enhance the efficiency and reliability of experimental investigations by systematically planning, conducting, and evaluating controlled experiments. To support well-informed decision-making, process optimization, and quality improvement, the main goal of DOE is to discover and quantify the effects of various variables on a response variable. Various methods such as full factorial, fractional factorial, Taguchi, and response surface methodologies provide powerful tools for optimising processes and enhancing quality. The study covers the application of DOE in several industries, including engineering, manufacturing, agriculture, and medicine. Defect minimization, process optimization, and quality improvement are all aided by DOE in manufacturing. By determining the best dosages and formulations, it helps in drug development in the pharmaceutical industry. In the field of agriculture, DOE facilitates the identification of optimal growing conditions and techniques. It helps in the engineering and assessing new systems and products. To achieve consistency and accuracy in data collection, the experiment must be carried out with strict adherence to the experimental strategy. Analysing data involves using statistical tools to evaluate the findings and make conclusions, such as ANOVA, regression analysis, and graphical approaches. By pointing out important variables and their interactions, these studies aid in process optimization and product quality enhancement.

Keywords: DOE; factorial design; fractional design; Taguchi method; methodology

1. Introduction

DOE is a statistical methodology used for planning, conducting, analyzing, and interpreting controlled tests to understand how various factors influence a response variable. The origin of this methodology goes back to the early days of statistics when agricultural experiments were being made, but the modern framework was defined by Sir Ronald A. Fisher in the 1920s and 1930s. He introduced such core ideas as randomization, replication, and blocking and developed an analysis of variance to compare several groups [1].

Factorial designs with DOE make the research of several factors simultaneously fast and effective; therefore, they add depth and reliability to the findings from experiments. More complex designs and analyses became possible with the availability of computers during the second half of the 20th century and, in turn, gave way to higher methodologies like response surface methodology (RSM), optimal designs, and adaptive designs.

Nowadays, it finds a broad range of applications in almost every sector: engineering, agriculture, pharmaceuticals, social sciences, and so on. The introduction of modern statistical software tools such as SAS, JMP, R, etc. has certainly made the working of DOE very easy by assisting the researcher to design better experiments, analyze data according to one's requirement, and arrive at meaningful conclusions with much ease and accuracy. The foundations laid by Fisher continue to underlie the field, driving innovations and applications in experimental research [2].

DOE is a branch of applied statistics that deals with planning, conducting, analysing and interpreting controlled tests to evaluate the factors that control the value of a parameter or group of parameters. It can be applied whenever you want to investigate a phenomenon to gain understanding or improve performance. We risk being forced to continue with the costly and time-consuming trial-and-error method in the absence of a proper DOE. As a result, DOE is an effective, well-organized, and structured instrument for correlation between variables (X) that influence a chemical analysis or process and are gauged by their results, such as process yields or experimental means (Y) [2].

For the last two decades, DOE has traditionally been a very useful tool for the betterment of product quality and reliability [2]. In many industries, the usage of DOE has been increased as part of the decision-making process along a new product development and its manufacturing process and improvement. It is not used in only engineering areas it has been used in administration [3], marketing [4], hospitals [5], pharmaceutical [6], food industry [7], energy and architecture [8,9], and chromatography [10]. DOE applies to physical processes as well as computer simulation models [11].

2. Background of DOE

The complex and multi-century history of DOE has been shaped by the efforts of numerous scientists and statisticians. The origins of DOE can be traced back to the early 20th century, In the 1920s, British statistician Sir Ronald A. Fisher, considered the father of modern statistics, developed the first designed experiments using two planting fields for multivariable testing to boost crop yield. His work laid the foundation for modern DOE techniques, such as analysis of variance (ANOVA) and the development of statistical models. Fisher also invented the idea of factorial designs, which let scientists look at the impacts of several variables at once. Insights into the interconnections between elements are provided by this method, which is more effective than examining each aspect independently [1].

Shewhart, an engineer and statistician, is well recognized for his contributions to statistical process control and the utilization of control charts to monitor process quality. Among their contributions to DOE are the development of the conventional deviation control chart and the idea of statistical tolerance limits.

During World War II, statistician George E. P. Box of Imperial Chemical Industries in the United Kingdom applied Fisher's theoretical framework to evaluate German nerve gas. He then talks about how DOE is applied in business. In 1978, Box coauthors the seminal book on DOE, "Statistics for Experimenters," with William Gordon Hunter of the University of Wisconsin, Madison, and John Stuart Hunter of Princeton University, who had previously worked at American Cyanamid [12].

After the Second World War, in 1980, a Japanese engineer by the name of Genichi Taguchi developed a method for organizing studies to find out how different variables affect the mean and variance of a process performance characteristic that shows how well the process is working. Taguchi presented an experimental setup wherein orthogonal arrays are used to arrange the process parameters and their corresponding levels. The Taguchi technique is a substitute for evaluating every conceivable combination, as the factorial design does, by testing pairs of combinations. This results in time and cost savings by enabling the acquisition of the necessary data to pinpoint the factors that most influence the quality of the final product with the least number of samplings. When there are an intermediate number of variables (3 to 50), a small number of significant contributing variables, and few interactions between variables, the Taguchi technique performs well [13].

Jack Welch of General Electric popularized Six Sigma in the 1990s after it was created by Motorola in the 1980s. Six Sigma uses statistical tools and techniques to improve process quality and lower faults. The "Improve" step of the DMAIC (Define, Measure, Analyse, Improve, Control) cycle is when the DOE becomes crucial in Six Sigma. With the use of DOE, practitioners can systematically ascertain the relationship between influencing factors and process outputs, allowing for process improvement for improved quality and efficiency. Ensuring strong process improvements and long-lasting quality upgrades, this methodology's structured approach aids in identifying crucial factors and their interconnections [14].

DOE internal training for other sectors was first offered by DuPont's Quality Management & Technology Center in the 1970s. This campaign played a major role in the widespread adoption of DOE methodologies. Throughout the 1990s, DuPont remained committed to DOE, demonstrating its practical benefits in process improvement and quality control. Throughout the 1990s, the business kept up its service [15].

A DOE-based quality management strategy known as Quality by Design was outlined in 2011 by the Food and Drug Administration. In New Drug Applications, the FDA expressly encourages the use of multivariable data. Improved medicine quality and secure supply chain operations are the agency's two main goals [16].

3. Methodology

This methodology outlines a structured approach for conducting an Experimental study. The primary aim is to ensure robust analysis through a comprehensive process of data collection, organization and hypothesis testing. The process begins with defining the specific parameters to be studied. This includes determining the inputs and outputs of the experiment and ensuring a clear understanding of the variables under investigation. Once the parameters are identified, the next step involves selecting the levels for each parameter. This is followed by choosing a suitable DOE method to systematically vary the parameters. The choice of DOE is critical as it influences the efficiency and reliability of the data collected. With the DOE framework in place, the experiment is run to gather data. This involves executing the planned tests and ensuring that all relevant data is accurately collected. Post-experiment, the collected data is organized systematically. This step is essential for ensuring that the data is clean and ready for analysis. Before proceeding with hypothesis testing, the normality of the data is assessed. This is a crucial step as it determines whether parametric or non-parametric tests should be used. If the data follows a normal distribution, parametric tests are applicable, otherwise, non-parametric tests are considered. Based on the normality check, a suitable statistical test is selected. The hypothesis is then formulated, and the test statistic is estimated. The critical value is determined to decide whether to accept or reject the null hypothesis (Ho). If the null hypothesis is rejected, a post-HOC test is conducted to identify specific differences between groups or treatments. If the null hypothesis is accepted, it concludes that there is no significant difference, and the process ends. The final step involves drawing conclusions based on the test results (see **Figure 1**). The findings are summarized, and relevant insights are provided, which form the basis for recommendations or further research.

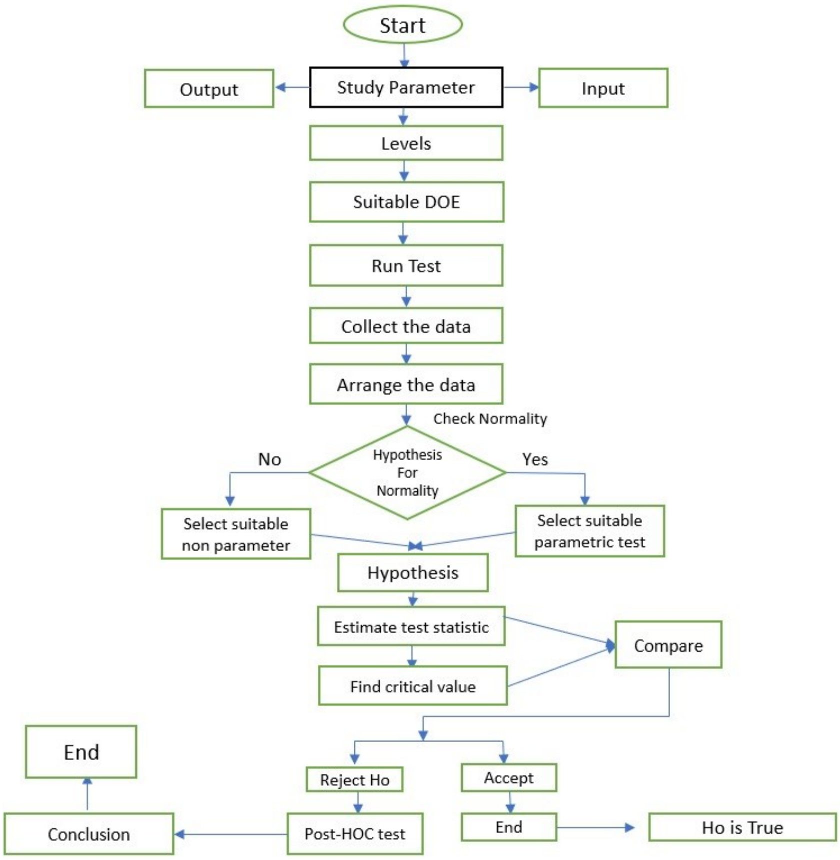

Figure 1. Flowchart of DOE.

The Taguchi method employs various types of quality characteristics or responses to evaluate the performance of a system or process. These include ‘smaller is better,’ ‘larger is better,’ and ‘nominal is better.’ The ‘smaller is better’ criterion is applicable when minimizing the output parameter is desired, such as reducing defects, errors, or manufacturing variations. ‘Larger is better’ is relevant when maximizing the output parameter is preferred, as in cases of strength, durability, or speed. Finally, ‘nominal is better’ is suitable when a specific target value for the output parameter is necessary, such as achieving precise dimensions or tolerances in a part [17].

- Smaller the better

$$\frac{\mathrm{S}}{\mathrm{N}} = -10\log\left(\frac{1}{n} \times \sum_{k=1}^{n} y_k^2\right) \tag{1}$$

- Larger the better

$$\frac{\mathrm{S}}{\mathrm{N}} = -10\log\left(\frac{1}{n} \times \sum_{k=1}^{n} \frac{1}{y_k^2}\right) \tag{2}$$

- Nominal the better

$$\frac{S}{N} = -10\log\left(\frac{\overline{Y^2}}{s_k^2}\right) \tag{3}$$

where:

y_k: Output values
n: Repeated number of trails
$\bar{Y}$: Mean of output values
s_k^2: Variance

Full factorial design (FFD) examines all possible combinations of factors, yielding extensive data but necessitating numerous experimental runs. Fractional factorial design decreases the number of experiments by concentrating on significant interactions, enhancing efficiency for complex systems. The Taguchi method streamlines the process by employing orthogonal arrays, allowing the investigation of multiple factors concurrently with fewer runs. RSM is frequently utilized for optimization, modeling the relationship between input factors and output responses to forecast the optimal conditions [18–25].

4. DOE in optimization

Fused Deposition Modeling (FDM) is a widely used 3D printing technique, yet achieving optimal mechanical properties in printed parts can be difficult due to the impact of various printing parameters on residual stress. Residual stress, a crucial factor influencing part performance, has been extensively studied. Recent research employed Digimat-AM software to simulate and predict residual stress in ABS materials printed through FDM, revealing that parameters such as printing temperature, speed, and infill percentage have a positive correlation with residual stress, whereas layer thickness shows a negative correlation. Bed temperature had minimal effect. The study emphasizes the concentric infill pattern as the most effective for reducing residual stress, providing valuable insights for process optimization in FDM [26].

Selvam et al. (2022) investigated the optimize Fused Filament Fabrication (FFF) parameters to improve surface quality and decrease printing time for Acrylonitrile Butadiene Styrene (ABS) polymer using statistical and optimization techniques. The analysis utilized ANOVA, RSM, and Particle Swarm Optimization (PSO) to predict optimal values for layer thickness, printing speed, and nozzle temperature. A central composite design was employed for the experiments, and mathematical models were created to evaluate the relationship between input parameters and output responses. WASPAS ranking indicated that PSO outperformed RSM, achieving optimal printing parameters with enhanced surface quality and reduced printing time. This study provides valuable insights for optimizing FFF processes, especially for ABS polymers [27].

A rapid, green, and efficient RP-UPLC method was developed and optimized using a FFD for the simultaneous separation of oseltamivir phosphate, daclatasvir dihydrochloride, remdesivir, and dexamethasone as co-administered drugs. Separation was achieved on a BEH C18 column with precise retention times for each compound. The method demonstrated excellent linearity, accuracy, and precision, with recovery rates exceeding 99.5%. The limits of detection and quantitation were low, ensuring high sensitivity. Two novel approaches were introduced: one for assessing solution stability and another for evaluating excipient interference using an innovative instrumental standard addition method. This eco-friendly method, supported by high Eco-score, GAPI, and AGREE criteria, provides a sustainable and time-efficient solution for drug analysis in pharmaceutical formulations [28].

Glass-filled polyamide (GF/PA) is extensively utilized in the automotive industry due to its exceptional mechanical, thermal, and physical properties. However, producing high-quality functional parts through Selective Laser Sintering (SLS) remains a challenge, as the quality of the parts is significantly influenced by sintering conditions. Negi et al. (2023) studied have concentrated on optimizing these parameters to enhance properties such as density and hardness. By employing a DOE approach, key sintering parameters were statistically evaluated for their effects on the hardness and density of PA 3200 GF composites. The results indicated that low energy density resulted in weak particle interaction, which diminished material integrity, hardness, and density. This research aids in optimizing SLS parameters for improved part quality in GF/PA composites [29].

RSM is extensively utilized for optimizing process parameters in casting, welding, and machinability studies of composite materials. RSM offers significant advantages in experimental design, as it minimizes the number of experiments needed for a given set of factors and levels, providing several benefits over the Taguchi method. Experiments are conducted according to the design, and the output responses are recorded. ANOVA is employed to identify the factors that significantly influence the response. Regression models are subsequently developed to predict responses, and the process parameters are optimized to achieve a specific objective function [30].

Metal Matrix Composites (MMCs) are widely used in industrial applications due to their exceptional mechanical properties. Traditional machining methods are inadequate for hard materials and composites, leading to the adoption of nonconventional techniques such as Electrical Discharge Machining (EDM). Gugulothu et al. (2024) investigated to optimize the EDM process variables for Al5456/SiC/Flyash hybrid composites, investigating the effects of pulse-off time, current, and pulse-on time. Central Composite Design (CCD) based RSM was utilized for experimentation. Material removal rate (MRR) and surface roughness (SR) were modeled using CCD, while ANOVA revealed that current and pulse-off time are the most significant factors affecting MRR and SR. Validation results indicated maximum

MRR and SR of 0.783 mm^3/min and 13.26 µm, respectively, with regression models and 3D/contour plots assisting in predicting and evaluating responses [31].

5. Applications

5.1. DOE in the field of Agriculture

In low-input agriculture systems of West Africa, nutrient deficiency and poor soil structure hinder crop production. A study in Burkina Faso evaluated compost's impact on crop yield and soil properties at Mediga and Yimtenga sites using Randomised Block design (RBD). Compost applications of 10 Mg ha−1 and 5 Mg ha−1 significantly increased soil cation exchange capacity and pH, with sorghum yields tripling and rising by 45% respectively. Additionally, compost mitigated the negative effects of delayed sowing. Despite these benefits, socio-economic challenges such as lack of equipment, materials, and intensive labour hinder widespread adoption. Addressing these constraints could enhance food security in the Sahel region [32].

Spatial variation in soil and related factors often significantly affect the outcomes of agronomic field experiments. While the RBD is the most prevalent, it can be inefficient, leading to inflated error terms. Alternative experimental designs, such as the Latin square (LS), allow for bidirectional blocking, potentially accounting for spatial variability more effectively. This study aimed to investigate the occurrence of two-way gradients in agronomic field trials and compare the estimated relative efficiency (ERE) of LS to RBD. Thirty LS trials were conducted across 10 states in the midwestern United States in 2013, focusing on the crop yields of corn (Zea mays L.), and soybean (Glycine max (L.) Merr.), and sorghum [Sorghum bicolor (L.) Moench]. Results indicated that 47% of the trials exhibited a two-way gradient, suggesting this characteristic is widespread across a large geographic area. The LS design increased the ERE in 70% of the trials, while a lower ERE was observed in only 7% of the trials. The prevalence of multiple gradients in agronomic field plot trials and the significant variation between the two blocking directions justify the use of the LS design. The data suggest that the LS design offers a low-risk, high-reward option for controlling spatial heterogeneity and increasing precision. Therefore, when the trial area appears uniform and gradients are not obvious, the LS design should be preferred in field experiments [33].

This investigation compared Egyptian cotton (Gossypium barbadense L.) genotypes for yield and its components in the Delta and Upper Egypt during 2009 and 2010. Two groups of long-staple cotton were evaluated using a 4 × 4 Latin square design at each location. In the Delta, variety 10229 × G86 significantly outperformed G86 for yield, seed, and lint indices, while in Upper Egypt, cultivar G80 surpassed G90 × Australian for yield components. Insignificant differences in fibre properties were observed. The combined analysis of variance for both regions indicated that 10229 × G86 was the best variety in the Delta. A significant difference was noted between cultivars and varieties for seed and lint yield. This study highlights those multiple analyses of Latin square designs is effective for assessing variance among genotypes across different regions, offering advantages over traditional combined analysis for regional cotton programs [34].

Activated carbon (AC) was prepared from rice husk through chemical activation, employing factorial design to optimize the process beyond the capabilities of single-variable changes. Characterization of the AC included N2 adsorption/desorption and surface group titration. The study achieved AC with a high surface area (up to 1593 m^2/g), significant mesopore volume (up to 1.22 cm^3/g), and notable surface acid groups (up to 4.4 mmol/g). These features are crucial for applications in adsorption and acid catalysis. The results demonstrate that factorial design is an effective tool for producing AC from rice husk with desirable properties, confirming its potential for various industrial applications [35].

Zha et al., (2020) designed a six-row centralized pneumatic deep precision fertilization device for rice trans-planters, featuring a spiral fertilizer distribution system, centralized pneumatic delivery, an opener system, and a control system using photoelectric sensors and PID algorithms for precise fertilization. Tests showed the centralized airflow distribution method had a low coefficient of variation (1.67%), with fertilization consistency and stability coefficients of 1.49% and 2.86% at specific speeds. Dynamic tests had a maximum relative error of 2.00%, while field tests showed an average relative error of 3.53%, meeting design standards. This work aids in optimizing pneumatic precision fertilization systems [36].

Poor crop yields are a major concern globally, particularly in Nigeria, where inadequate agricultural produce affects both the local market and export potential. Corn (Zea mays), essential for various products like animal feed and corn flakes, is especially in demand. Akanihu et al. (2023), employed a split-plot design with five replicates to maximize corn yield, considering soil types (clay, sandy, loamy) and fertilizer types (NPK 15/15/15, Urea, Golden 20/10/10) as factors. A linear regression model showed that loamy soil significantly outperformed sandy and clay soils. Among fertilizers, NPK 15/15/15 on loamy soil resulted in the highest yield. The study, supported by Taguchi analysis, concluded that the combination of NPK 15/15/15 fertilizer and loamy soil is optimal for maximizing maize yield in Nigeria, offering a strategy to improve agricultural productivity and affordability [37].

5.2. DOE in the field of engineering

The modern construction industry has benefited greatly from technical improvements, which has made welding an essential component of metal engineering and repair. Elevated proficiency in welding is vital for amalgamating metallic constituents, guaranteeing superior adhesion. To identify the variables influencing weld quality, the DOE method has been used. Welding amperage, welding technique, electrode type, plate thickness, and welding speed are important control elements. Workpiece cleanliness, distance between workpieces, and the welder’s skill level are examples of noise-related factors that affect results. ANOVA and DOE calculations have been used in studies to demonstrate that although welding speed has no significant effect on weld quality, other parameters such as electrodes, welding amperage, plate thickness, and welding techniques do. It is important to precisely regulate these variables to remove faults and assure optimum weld quality, as the best welding results were obtained under a specific trial environment [38].

Although the DOE provides protocols and principles, it does not provide comprehensive methodologies for choosing the best DOE from a wide range of options. This study fills this vacuum by analyzing more than thirty distinct DOEs over almost half a million simulated experimental runs. This study uses the FFD as a benchmark and focuses on the thermal behavior of a double skin façade (DSF). The most efficient designs are determined by comparing the performance of different DOEs. The study produces general findings about how various DOEs behave that go beyond the particular case study. A broad decision tree chart and recommendations are provided to help choose appropriate DOEs based on these insights. By using DOEs that take into consideration the nonlinearity and interaction of various process variables, this study helps researchers and designers choose the most effective and successful designs for particular process characterizations [39].

The dependability and longevity of proton exchange membrane fuel cells (PEMFCs) are dependent on several complex Multiphysics factors, including mechanical, electrical, chemical, and thermal ones. A Multiphysics model and DOE are used in this paper's theoretical and numerical investigations to optimize fuel cell performance. An electrical resistance prediction for the fuel cell is suggested using a 3D finite element study that includes a fully connected thermal-electrical-mechanical model. To optimize fuel cell performance under various conditions, DOE approaches are used, given the uncertainties in mechanical parameters such as the bipolar plate's bending radius, the thickness of the Gas Diffusion Layer (GDL), and the clamping pressure. This technique delivers a thorough grasp of how various factors interact and affect fuel cell performance, offering insightful information that can be used to improve the efficiency and dependability of PEMFCs. The outcomes set the stage for more investigation and useful fuel cell technology applications technology [40].

Material Extrusion (MEX) technology, a crucial additive manufacturing (AM) method, has garnered significant attention for its potential in producing complex geometries. However, enhancing surface quality and mechanical properties continues to pose a challenge. Post-processing techniques, particularly the ironing process, have been investigated to overcome these limitations. Recent studies, including those utilizing DOE and Box-Behnken Design (BBD), have shown the effectiveness of optimizing ironing parameters. Alzyod and Ficzere (2024) indicates that optimized ironing markedly reduces surface roughness and improves mechanical properties, such as Ultimate Tensile Strength (UTS), compressive strength (CS), flexural strength (FS), and impact strength (IS). These advancements highlight the significance of post-processing in enhancing the performance and aesthetic quality of MEX-manufactured components [41].

Fused Deposition Modelling (FDM) is a widely used additive manufacturing technique for producing 3D prototypes directly from STL models. Despite its benefits, FDM is susceptible to residual stresses caused by rapid heating and cooling cycles during filament deposition, resulting in warping and distortions in printed parts. Various printing parameters, such as printing orientation, raster angle, and infill pattern, affect the mechanical properties and residual stress in FDM components. While experimental investigations of these parameters can be expensive and time-consuming, recent studies have examined numerical solutions to better understand their effects. Findings indicate that printing orientation has the most substantial impact on residual stress, followed by raster angle, with infill pattern exhibiting minimal influence [42].

Warping deformation remains a significant challenge in ABS additive manufacturing, particularly in material extrusion processes, as it impacts both dimensional accuracy and part quality. Previous studies have emphasized the necessity of optimizing printing parameters to mitigate warping. Alzyod and Ficzere (2023) adopts a simulation-based approach utilizing numerical techniques and Digimat-AM software to analyze warping deformation. Parameters such as bed temperature, chamber temperature, printing speed, and printing temperature were examined. By employing the Taguchi method for experimental design, the study identified bed temperature as the most influential factor, followed by chamber and printing temperatures. These findings offer a solid framework for optimizing process parameters to enhance the dimensional accuracy and performance of ABS-printed parts in additive manufacturing [43].

5.3. DOE in the field of financial domain

The Capital Asset Pricing Model (CAPM), which prioritizes market return, beta, and the risk-free rate, is essential for evaluating predicted investment returns. Although it's difficult to pinpoint a single, dominant element because these factors interact in intricate ways that are influenced by a variety of market dynamics and investor moods. Though it offers a basic structure, CAPM includes several significant presumptions and restrictions. Additional factors that impact real-world asset pricing include liquidity, market efficiency, and firm-specific hazards. These are not included in the CAPM. Practitioners frequently add more variables and models to CAPM to improve forecasting accuracy. It is for this reason that the application of CAPM needs to be critically assessed. Alternative strategies that take into account behavioral subtleties and practical complications are encouraged for examination by researchers and investors. Improving asset pricing models along with offering investors with additional guidance depend on policy actions to increase market efficiency, lessen information asymmetry, and increase investor education [44].

The number of nodes in an artificial neural network (ANN) is one of 27 possible financial and economic variables that are used in DOE to find statistically important factors among them. The research shows that ANNs using the most significant features are able to predict the S&P 500's daily direction more precisely than logit models. Compared to the buy-and-hold approach, the use of this optimized ANN during the test period shows a notable increase in trading earnings [45].

Through its ability to enhance trading performance and estimated accuracy, DoE has been shown in this study to be successful at fine-tuning ANNs for financial forecasting. According to the findings, more trustworthy financial models may result from rigorous variable selection and DoE optimization. For financial analysts and traders interested in maximizing returns, this technique is a useful tool because it not only enhances forecasting ability but also provides useful advantages in trading tactics [45].

The article expands these methods when applied to accounting and finance while highlighting the significance of field experiments in establishing causal links within economics. It tackles crucial behavioral factors and experimental design by offering a thorough manual on carrying out field studies, including producing and evaluating data. This study highlights important issues and points to areas that warrant additional research, drawing on field trials that are already underway and pertinent to accounting and finance. Field experimentation is essential for developing a deeper understanding of intricate financial and accounting difficulties, according to the study's conclusion, which also suggests that DOE can significantly improve empirical discoveries in these domains [46].

By applying a DOE methodology, this study investigates the economics of charitable fund-raising by testing theoretical hypotheses about the ideal lottery design. The research paper establishes a more precise simulation of contributor behavior by easing the assumptions of risk-neutrality and preference homogeneity. Following several experimental treatments, it was determined that single- and multiple-prize lotteries perform better than the voluntary contribution method in terms of the amount of money raised overall and the number of contributors. The outcomes emphasize how crucial it is to take choice heterogeneity and risk postures into account when creating fund-raising methods. DoE can be used to evaluate and improve economic theories in the field of finance through empirical research, as demonstrated by this study. According to the findings, fund-raising tactics ought to be customized to the unique risk profiles and preferences of possible donors. This illustrates the flexibility and usefulness of DoE in financial research while demonstrating its ability to maximize fund-raising tactics through empirical validation [47].

This paper relies on a DOE methodology to seek out the influence of ambiguous attitudes on the willingness-to-pay (WTP) for index insurance among female smallholders in Kenya. The article uses metrics that are compatible with incentives to evaluate ambiguity aversion, insensitivity to gains and losses, and loss aversion. By offering a "rebate" insurance option to a subsample, a framed experiment will be carried out to calculate WTP for insurance with base risk. In line with theoretical predictions, the results demonstrate that loss aversion substantially lowers WTP for standalone insurance, however ambiguity aversion greatly raises it. This result suggests that weather unpredictability may generate more disutility than insurance ambiguity, which is in contradiction to previous field research. Differences in insurance experience are the reason for the discrepancy, emphasizing the function of insurance as a mediator. According to the intricacy of the binding agreements, the rebate insurance circumstances helps increase the influence of ambiguity aversion while lessening the impact of loss aversion on WTP. The current research investigation highlights the value of familiarity and experience when influencing customer choices by demonstrating the applicability of DoE in comprehending behavioral reactions to financial items. The expected results highlight the complex interactions among ambiguity, loss aversion, and product familiarity, granting valuable information for creating safe financial products in high-risk situations [48].

5.4. DOE in the field of medicine & research

When the factors influencing printed form features are not fully understood, fused deposition modelling (FDM) is a popular 3D printing technique in the pharmaceutical business. To determine the effects of a pore former (mannitol, 0% or 10%), infill percentage (50% or 100%), and drug percentage (5% or 10%) on 3D-printed forms utilizing dexamethasone and poly (ε-caprolactone), this work used a DOE technique. Findings show that pore former and infill percentages considerably affect drug release rates, which are in line with the Higuchi model. DoE is devoted to studying and demonstrating that manipulating these parameters can tailor drug release profiles, hence augmenting the creation of customized tumour implants and refining oncology drug delivery systems [49].

Several obstacles, including complexity, regulatory approvals, and upscaling expenses, make pharmaceutical bioprocess optimisation challenging and could result in less-than-ideal drugs. Achieving the intended results necessitates keeping an eye on several factors because of their inherent complexity. Bioprocess optimization greatly benefits from the statistical DOE, a crucial part of the quality by design (QbD) methodology. Statistics from DoE are crucial for comprehending how important process variables affect quality attributes. Showcasing the benefits of DOE, this review brings together publications that use it to optimize bioprocesses. Effective DOE utilization can improve bioprocess robustness, efficiency, dependability, and quality; in the end, this will improve patient outcomes and the general quality of the bioprocess [50].

The article focuses on the use of DOE to optimize biotechnology linked to bioprocesses, specifically media optimization for the production of enzymes, antibiotics, and recombinant proteins. DoE approaches are frequently used for increasing productivity and product yield because of their efficacy and simplicity. Examples of these techniques are response surface modelling and factorial designs. However, the review reveals that DoE is not being completely utilized. Complex needs such as recombinant protein induction and embryonic stem cell differentiation can be addressed using sophisticated factorial design and statistical analysis. The focus of Process Analytical Technology (PAT) is on enhancing bioprocess optimization through the investigation of inherent biological reactions and interdependencies. Furthermore, improving analytical evaluations through the integration of data mining tools can progress the development of bioprocesses [51].

By examining both empirical and theoretical case studies carried out in Batman City and Istanbul (2013–2014), this article studies the use of DOE in the healthcare industry. The study determines important elements impacting results, such as interactions specific to each patient and the severity of the malignancy, using the Design Expert Program. Using Gaviscon and Protech medications, the study shows how DoE can reduce noise sources, improve model parameters, and produce the best outcomes in healthcare settings. The potential of DoE in healthcare has not yet been completely realized, despite its past applications. DoE can improve healthcare outcomes, as this study's thorough visual and statistical analysis demonstrates [52].

A robust approach for boosting the effectiveness and caliber of healthcare services is the combination of Discrete Event Simulation (DES) and Lean Healthcare concepts. The article planned the growth of a Canadian emergency department (ED) to meet the demand from smaller closed-care clinics by utilizing DES and Lean principles. The optimum amount of sites and resources for each shift was ascertained through the use of DOE and the FlexSim Healthcare® software. Studies have demonstrated the efficacy of combining DES with Lean principles to optimize healthcare operations, with the percentage of fully treated patients rising from 17.2% to 95.7% and the average Length of Stay (LOS) falling by 79.0%. The ability of DoE to pinpoint significant factors along with making data-driven choices to improve the provision of healthcare services is demonstrated by this study [53].

5.5. DOE in the field of marketing & business

Distinguished products are essential to grab customers and increase market share in a cutthroat international industry. Marketing creates the desire for consumer-pleasing items, and the DOE is an essential process for creating, refining, and enhancing products and procedures to satisfy these needs. Product developers and engineers may optimize designs even in resource-constrained contexts because of DOE's efficiency and depth of information. Aligning product qualities with customer needs is made possible by the insights obtained through cycles of continuous improvement and DOE methods. To demonstrate how well DOE develops products that meet marketing goals, this article offers three case studies [54].

In addition to promoting the proper application of DOE, this study aims to clarify illusions regarding its utility. While utilized in a timely and economical manner, DOE is an effective method to enhance both process and product quality. To optimize the benefits of DOE, this paper demonstrates its correct implementation, as misapplications and improper behaviours might limit its potential. The study emphasizes the successful implementation of DOE in product and process development, which will eventually result in better outcomes and resource optimization, by highlighting best practices and resolving typical difficulties [55].

Technologists and economists need to use strategic techniques to tackle the problems of quickly changing markets with demanding customers and shorter product life cycles. To comprehend how changes in an input variable affect system outputs, DOE is essential. DoE finds relationships between process factors, as opposed to the conventional one-factor-at-a-time (OFAT) approach. utilizing a case study on the production of rubber gloves, this paper highlights interactions whose services are hidden from OFAT and proves the efficacy of DoE. DoE's superiority in process optimization is illustrated by the generated model, which highlights areas for operational improvement by illuminating the links between input and output variables [56].

In addition to providing guidance and recommendations for researchers in the field, this study thoroughly examines the use of field experiments in marketing research. The articles hope to encourage the use of field experiments as a preferred research method in marketing and finance by emphasizing their advantages and methods. The significance of DOE is highlighted as a potent instrument for comprehending consumer behavior, refining marketing tactics, and enhancing financial models. DoE renders it possible for scientists to find intricate relationships between variables, producing more precise and useful discoveries. The importance of DoE in furthering marketing and finance research and practice is highlighted by this review [57].

5.6. DOE in the field of food & beverages industry

In the food sector, where waste reduction, profitability, and technological advances are critical, efficient resource usage is critical to industrial experimentation. Leveraging the bare minimum of time and resources possible, the Taguchi DOE provides an advantageous approach for optimizing important attributes. Using articles from the Scopus, Web of Science, and PubMed databases, this systematic study investigates the use of the Taguchi DOE in the food industry throughout the last 20 years. Only thirty-one pertinent papers were found, despite its benefits. Many research investigations fell short of realizing the full potential of the Taguchi DOE due to a lack of a systematic methodology and necessary instruments, highlighting important research gaps and opening doors for more reliable and scalable solutions in this field [7].

For the beverage industry to save money on transportation and extend product shelf life, it is essential to investigate the stability of concentrated oil-in-water emulsions. A 24-1 fractional factorial design was implemented in this study to investigate factors such as the ratio of lemon oil to water, starch, concentrations of Arabic gum, and dioctyl sodium sulfosuccinate, alongside the eventual objective of determining how primary components affect the stability of lemon emulsions. A comprehensive examination of the two most significant factors showed that emulsions including either Arabic gum or starch with a 50% lemon oil ratio demonstrated stability for more than 15 days. The primary outcomes showed that the surface tension ratio was greater than one and the viscosities of the stable formulations exceeded 100 cP. Through the methodical identification of essential elements impacting stability and the subsequent production of robust and efficient products, the study demonstrates the effectiveness of the DOE in enhancing beverage formulas [58].

In many sectors, mixture designs (MDs) and other DOE are vital statistical tools for product formulation and optimization. In the food, beverage, and pharmaceutical health industries, multiple uses of MDs are assessed in this analysis. The study finds that Brazil is the leader in MD applications, with America and Asia following closely after, using the PRISMA flow diagram and self-organizing maps (SOM) for data analysis. While MDs are more common in the health sciences in Asia, they are mainly employed in the food and beverage industry in the Americas. Doctors are skilled in creating medications for a range of illnesses as well as functional and nutraceutical goods. Even though MDs are widely used, there are still intriguing research areas where they could improve product optimization and development. In addition to noting areas that warrant further investigation, the above evaluation highlights the value of MDs in improving process effectiveness and product quality [59].

The food and beverage industry has discovered that combining DOE with Functional Data Analysis (FDA) has proven effective for streamlining complicated operations. To batch mill a hazelnut and cocoa paste in a stirred ball mill, the following investigation shows how to apply a face-centred central composite design. Using the integration of FDA, which i-ncludes data preprocessing, smoothing using the B-spline approximation, and using Functional Principal Component Analysis (FPCA), the study was able to accurately predict the functional responses (fineness and energy). Response surface modelling was used to create a dynamic design space based on the

FPCA scores. This strategy identified the rotating speed, ball mass, and diameter as the three main variables that affect product quality, enabling accurate control and optimization of the milling process. To simulate and optimize batch operations in food manufacturing, the results demonstrate the effectiveness and usefulness of merging the FDA and DoE [60].

6. Conclusion

DOE is a statistical tool that can be applied to many different industries. It provides methodical ways to optimize workflows, improve the quality of products, and increase productivity. By addressing soil variability and optimizing compost application, DOE in agriculture raises crop yields considerably. DOE discovers critical engineering parameters that impact fuel cell performance and weld quality. In the financial domain, DOE improves trading performance and asset pricing algorithms' forecasting accuracy. Because of its strong bioprocess and tailored drug release characteristics, DOE is beneficial to medical research. The food and beverage industry uses DOE to improve product formulation and stability, while marketing and business use it for product creation and process optimization. Across these domains, DOE proves its versatility and effectiveness in driving innovation and improving outcomes, underscoring its value as a critical methodology for empirical research and practical applications.

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