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The Impact of Some Computer Integrated Manufacturing Techniques in Achieving Production Efficiency

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Abstract:

Refers to the field reality for integrated manufacturing in Iraq, it needs to be developed Production efficiency in order to improve the quality level, reduce defects and errors, and control time and cost, there is a need to apply effective methods in this field. The goal of this study is to develop performance and improve quality integrated manufacturing by improving performance manufacturing resource planning systems in the hierarchical structure that begins with the institution, factory, cell, and production field, and implementation works manufacturing through line, star, tree, ring, controller area network For the purpose of achieving the objective of the study, the researchers relied first on the comprehensive theoretical study of the concepts of integrated manufacturing, and secondly on the field study carried out by

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the researchers by conducting an open questionnaire , we have been able to design a closed questionnaire based on 426 questionnaires.

Keywords: Integrated Manufacturing, Manufacturing Resource Planning Systems, Manufacturing Implementation Systems, Engineering Systems.

1. Introduction

Integrated manufacturing technologies are a set of technologies and methods aimed at improving production efficiency in manufacturing processes. These technologies are characterized by process integration and comprehensive automated control, and contribute to improving the quality of products, increasing productivity, and reducing the cost and time spent in the production process. Here we will provide an introduction to the impact of some integrated manufacturing techniques on achieving productive efficiency: Numerical control manufacturing (CNC): This technology relies on the use of computers and specialized software to control manufacturing processes. Allow pato manufacture via numerical control and by implementing processes with high precision and repeating them with the same quality over and over again, which contributes to improving production efficiency and reducing human errors. robotic manufacturing: robots are used in manufacturing processes to carry out repetitive and time-consuming tasks quickly and with high accuracy. Robots can perform work in hazardous or highly confined environments in place of human workers, reducing the risk of accidents and increasing production efficiency. 3D Printing: 3D printing technology is considered a revolution in the world of manufacturing, as it enables the creation of complex parts and various manufacturing tools faster and more efficiently. This technology can be used to reduce production costs and improve designs faster. Internet Manufacturing and the Internet of Things (IoT): Internet of Things technologies connect devices and equipment to a common network, allowing central monitoring and control of manufacturing processes, as and companies can monitor the performance of machines and equipment and predict breakdowns and required maintenance in advance, improving production efficiency and reducing unplanned downtime. AI Manufacturing: AI technologies help improve productivity by analyzing large amounts of data and extracting patterns and predictions. AI can be used to optimize production schedules, improve resource planning, and reduce loss and waste. In short, integrated manufacturing techniques play a vital role in improving production efficiency, reducing costs, and increasing quality in manufacturing processes. The main impact of these technologies is to improve control, accuracy, repeatability and reduce reliance on human labour, driving the manufacturing industry towards a more innovative and efficient future.

2. Literature Review

2.1. Previous studies:

In the production literature, the relationship between production quality and economic growth has greatly attracted economists and policy makers, and many studies have addressed this relationship through the use of three different types of data sets: time series, available alternatives, and numerical data and information.

Some previous literature has paid more attention to the role of production quality in economic growth, and providing integrated computer-aided manufacturing to reduce emissions. From the perspective of production quality and integrated manufacturing, (Koçak and Arkgünes¸2017) found that production quality has a positive impact on economic growth using integrated manufacturing. Berkeley Kamin (2006) also studied (The Impact of Integrated Manufacturing), which is a

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mathematical study that predicted economic revenues when. On CNC policies and measuring economic costs. However, the study overlooked the role of integrated manufacturing in achieving sustainable quality in its three facilities, maintaining continuous production improvement, and earning economic revenues, which are the essence of sustainable development and adopting applications of advanced technologies. (Apergis, Payne, 2012) [iv] developed a statistical model; Where the gross domestic product is the dependent variable, while the main explanatory variables are improving the quality of production from computer-integrated manufacturing sources and traditional manufacturing sources, the results revealed a two-directional relationship with production quality and the use of computer-integrated manufacturing, and gross domestic product, on short and long term. There was also a long-term bidirectional relationship between forms of CNC-integrated manufacturing, meaning that it is possible to switch between forms of CNC-integrated manufacturing.

Study of (Laith Hussain Kazem, Nofal Hussein Abdullaht) is based on the idea based on the fact that the change in the business environment and the emergence of many challenges are represented by a difference in the requirements and desires of customers, the openness of markets, the entry of information technology, and the emergence of counterfeit economic units, which leads to an increase in the intensity of competition between monetary units, which leads to monetary units to the need to search for new methods of manufacturing, in order to meet market requirements and preserve customers by introducing their requirements and needs into the design and production process in order to form a product that meets its ambitions, and for the success of economic units and maintaining their position in the market, It is necessary to provide Products that meet the needs and expectations of customers and at an appropriate cost.

2.2. Integrated manufacturing concept:

It is the system that includes the integration and design of product engineering and planning and manufacturing processes with the help of computer systems. Therefore, it is a program that relies on technology that includes design and production. It is called the technical factory for integrated visual and written communication mechanisms using computer programs (Jalal Delaram, Omid Fatahi Valila, 2018).

Integrated manufacturing is defined as the use of other advanced technologies to integrate and standardize various processes and systems in the supply chain and manufacturing process. Integrated manufacturing aims to achieve efficiency and continuous improvement by coordinating and controlling all production processes in an integrated manner. It is the use of computers and specialized software to control manufacturing processes, such as operating machines and cutting parts precisely according to code, which uses automated robots to carry out various industrial tasks accurately and quickly, which reduces human intervention and increases the efficiency of the process.

He also defined it as connecting devices and equipment to the Internet to collect data, improve productivity and performance of operations, analyze large amounts of data, make smart decisions, predict malfunctions, and improve the overall performance of operations.

As for (Sigifredo Laengle, Nikunja Mohan Modak, José M. Merigó & Catalina De La Sotta, 2018), he defined it as integrated supply chain management: coordinating and managing all stages of the supply, production and delivery process in an integrated manner to improve production efficiency and quality, and analyzing big data using analysis of the huge amounts of data generated during manufacturing processes to extract patterns and identify possible improvements.

These concepts combine technology and industrial processes to maximize efficiency and quality in manufacturing processes and enhance companies' competitiveness in the industry market.

2.3. The concept of production efficiency: top form

Definition (Yu-Qiang Chen a, Biao Zhou b, Mingming Zhang c, Chien-Ming Chen d,) is a concept that refers to the ability of companies and institutions to achieve the highest level of productivity using the least number of available resources. In other words, productive efficiency aims to achieve the greatest quantity of products or services with the least amount of labour, materials and time. Production efficiency is also considered an important indicator for measuring companies’ performance and their ability to compete in the market. If a company can increase productivity without increasing costs, it will be able to improve profit margins and achieve better competitiveness.

(Chunyang Yu a,b , Xun Xu b,⇑ , Yuqian Lu, 2015) defined it as the process of improving, simplifying and improving processes to reduce repetition, loss and waste, improving manufacturing speed and quality of products, and the use of advanced technology and advanced machines can contribute to improving efficiency and production accuracy.

(J. Delaram and O. Fatahi Valilai,2019) they defined it as resource planning, determining future needs for production, precisely determining the resources required to achieve the best performance, and quality control to improve inspection and monitoring processes and controlling the quality of products to avoid defective products and return work, while developing labor through training and developing labor to increase skills and experience and improve individual productivity to improve workflow, organize work effectively, and improve workflow to reduce interruptions and delays and improve the use of time.

Therefore, achieving production efficiency is not a constant job, but rather requires a continuous effort to improve processes, use technology, and develop human resources. By doing so, companies can improve their performance and enhance their competitiveness in the industry market.

3. Research Methodology

3.1. Importance of study:

The scientific importance of this study stems from the use of one of the commercial purposes in the field of integration, which is the role played by the successful management of logistics costs in improving the quality of production in light of the electronic operating environment, as the study is considered one of the topics and modern.

3.2. Goals the study:

The study aims to achieve a set of objectives:

1. Identify the impact of applying computer-based integrated manufacturing to achieve production efficiency in the factory.

2. Identify the extent of the impact of manufacturing resource planning systems on production efficiency.

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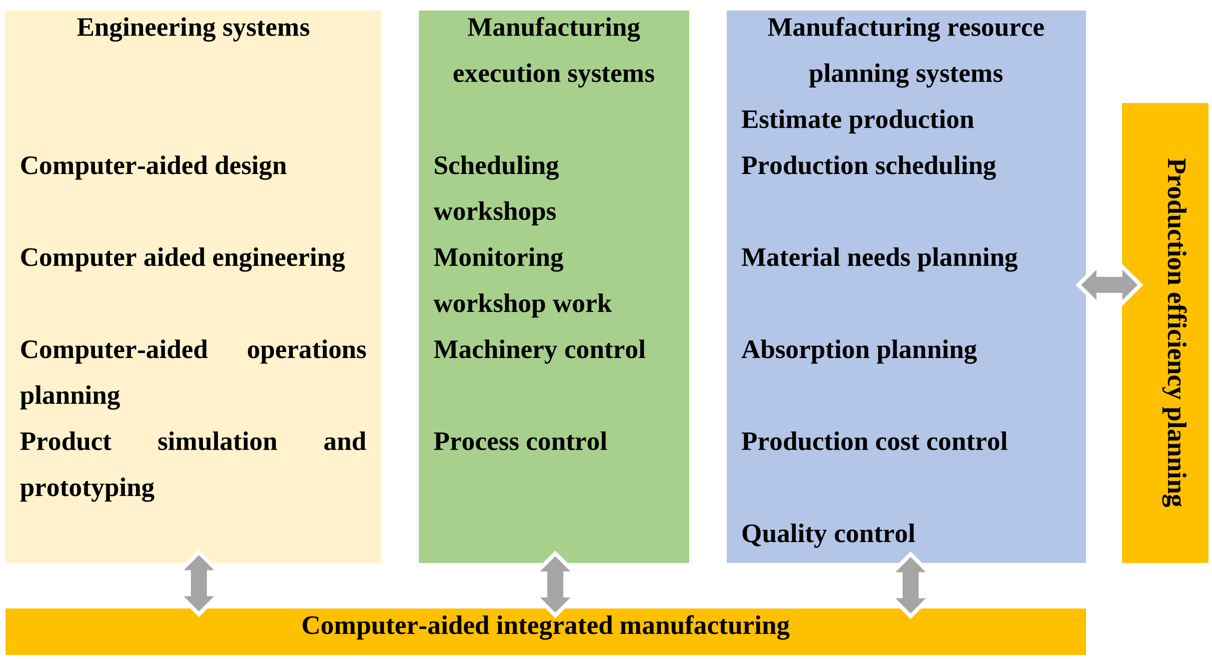
3. Identify the role played by software engineering and application software design organizations in increasing production efficiency and improving its quality.

4. Learn how to implement and operate integrated manufacturing.

The default form of the study:



3.4. Study hypotheses:

The current study adopted a set of hypotheses defined as follows:

Main hypothesis: There are no relationships impact moral between integrated manufacturing and between improving production efficiency a number of sub-hypotheses branch out from this hypothesis:

1. No Affects after manufacturing resource planning systems and improve production efficiency.
2. No Affect after implementing CNC integrated manufacturing and improving production efficiency.
3. Computer-aided engineering systems do not yet affect the improvement of production efficiency.

4. Results and Discussion

In this study, a non-standardized tool a process used to arrive at a group opinion or decision by surveying a panel of experts. Experts respond to several rounds of questionnaires, and the responses are aggregated and shared with the group after each round, was used to develop a questionnaire prepared by the researchers to measure the digital divide between crowds. By this process selecting reliable and valid scientific databases. And then to identify the relevant research in relation to the field of study, the sorting process was implemented in two stages: content analysis, and action steps analysis, in order to obtain a more specific understanding Fig. (1) was used.

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preparing

- defintion of research goals
- definition of additional questions

Conducting

- Selection of software tool
- Idetification of expert panel
- Collection of experts opinions and data

Analyzing

- Analyzing of dissent and sentiment
- Analying of estimests

Fig. 1. Analysis Process

The study is based on a cross-sectional framework using manufacturing data for different countries. Usually, hi and i are assumed to represent the technical achievements of CIM, ie the expected average output at the start of production in purchasing power parity (PPP), we assume that the definition of the minimum output for the levels of artificial intelligence and income Invested in a country will depend on the average purchasing power based on the method of use Artificial intelligence in industrial machines in that country. Therefore, we assume z to be a fraction λ(λ= 5%) and the gross domestic product of the product.

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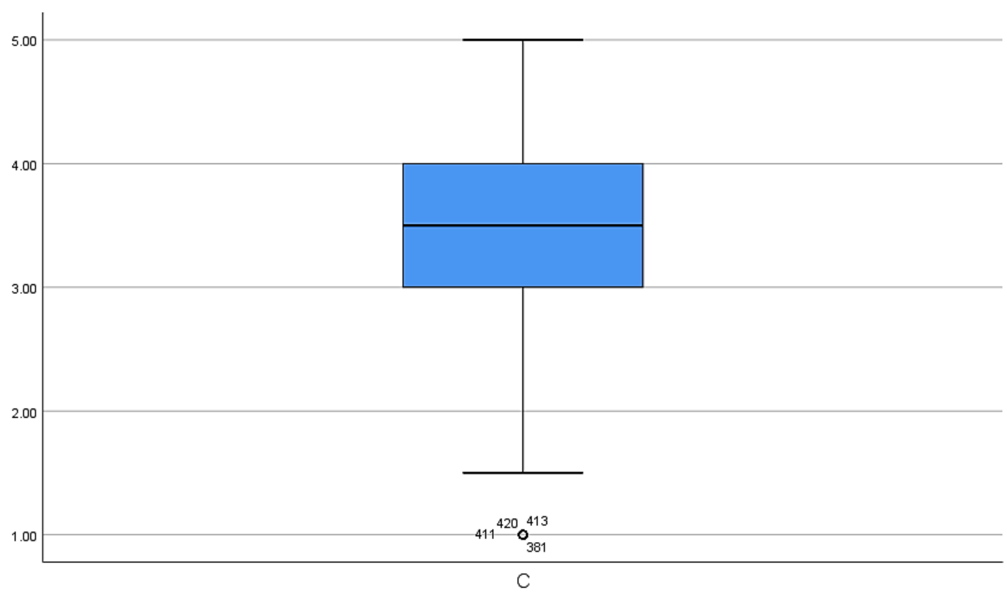
$$z_h = (1-\lambda)\bar{h}, \text{ with } \bar{h} = \frac{\sum_{i=1}^{N} h_i}{N}$$

and

$$z_r = (1-\lambda)\bar{r}, \ where\ \bar{r} = \frac{\sum_{i=1}^{N} gdp_i}{N}$$

where i = 1...N represents the number of countries in the region.



4.1 Testing the conceptual model and hypotheses:

Confirmative factor analysis (CFA) is a statistical method used in the social sciences to test the hypothesis that a set of observed variables (also known as indicators or items) measure the same underlying construct or factor. The aim of the CFA is to assess how well the structure of the putative factor is in agreement with the observed data. CFA is often used to test the fitness of a measuring instrument or to investigate the factor structure of a construction. In contrast to exploratory factor analysis (EFA), CFA identifies a number of factors in advance and tests a priori hypotheses about the relationships between factors and observed variables. Structural equation modeling using partial least squares and Smart-Pls method was used to analyze the research data. The software using structural equations modeling based on this statistical method complies with conditions such as alignment of independent variables, normality of data, and small sample size. The program outputs after testing the conceptual model of the research are shown in Figures (2). The following are the results of a two-part study: Measurement model test and Structural model test in detail.

For the purpose of analyzing the variables of the study, confirmatory factor analysis, constructive modeling, and the value of moral correlation were used by taking the opinions of a community sample consisting of professors and university students on the basis of the five-point Likert, where the questionnaire contained 21 questions that were adopted as variables and divided into independent variables (x1, x2, x3, x4, x5, x6, r1, r2, r3, r4, r5, h1, h2, h3, h4) represent integrated manufacturing and have axes that have been calculated, which are manufacturing resource planning systems, manufacturing execution systems, engineering systems, and variables dependent on the production efficiency variable (c1, c2, c3, c4, c5).

Structural equation modeling (SEM) is an important analysis of data, phenomena, and behaviors. The models were designed according to strategies to quantitatively describe the variables and their components, and then tested their validity and conformity of the design to field data, which were obtained by means of confirmatory factor analysis (CFA) as a tool for measurement and identification of

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variables. Relationships between latent variables that are inferred from dependent and independent variables.

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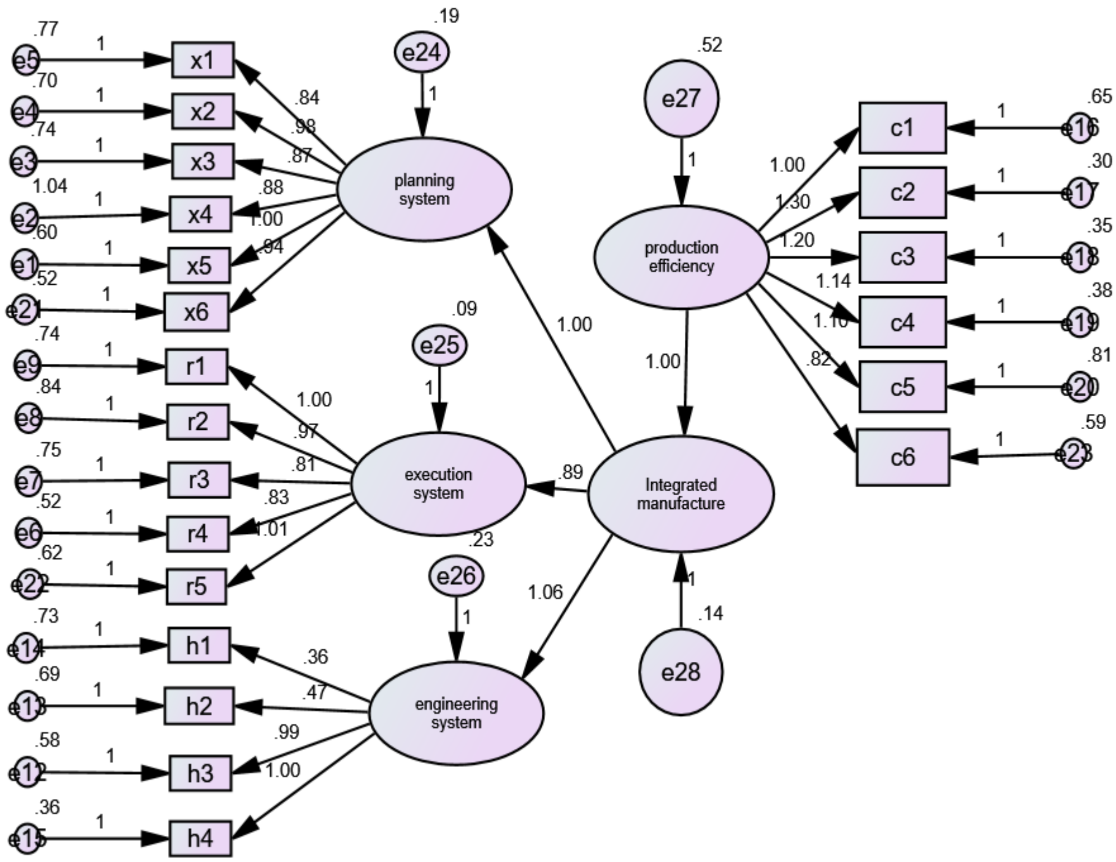

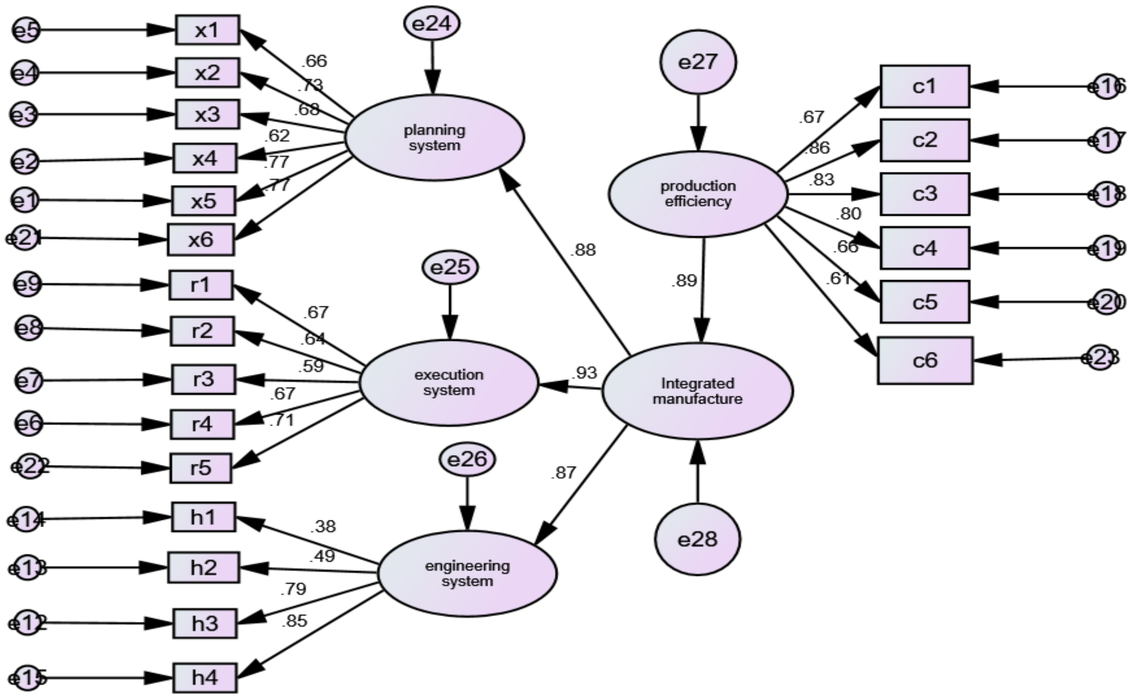

Fig. (2): Results of clinical factor analysis the researchers based on the results of the analysis (AMOS V26)

The default model presents the results of a chi-squared (χ^2) goodness-of-fit test for a Categorical data analysis, commonly used in statistics. The table no (1) shows the comparison of three different models in terms of various statistical measures:

NPAR: Number of parameters estimated in the model (66 parameters estimated), CMIN: The chi-squared statistic value for the model (1008.781), DF: Degrees of freedom associated with the chi-squared statistic (186 degrees of freedom), P : The p-value associated with the chi-squared test (p-value < 0.001), CMIN/DF: The ratio of CMIN to DF (approximately 5.424).

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The Saturated Model:NPAR: Number of parameters estimated in the model (252 parameters estimated), CMIN: The chi-squared statistic value for the model (0), DF: Degrees of freedom associated with the chi-squared statistic (0 degrees of freedom). Note that DF = NPAR in a saturated model, P: Since the degrees of freedom are zero, the p-value is not applicable.

CMIN/DF: Not applicable for a saturated model.

NPAR :The Independence Model: Number of parameters estimated in the model (42 parameters estimated), CMIN: The chi-squared statistic value for the model (4849.295), DF: Degrees of freedom associated with the chi-squared statistic (210 degrees of freedom), P : The p-value associated with the chi-squared test (p-value < 0.001), CMIN/DF: The ratio of CMIN to DF (approximately 23.092).

Table No. (1)

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	66	1008.781	186	.000	5,424
Saturated model	252	.000	0		
Independence model	42	4849.295	210	.000	23.092

4.2 Baseline Comparisons

Table No. (2) displaying different fit indices for three different models: the Default model, the Saturated model, and the Independence model. These fit indices are commonly used in structural equation modeling (SEM) and latent variable analysis to assess how well a model fits the observed data. Let's break down the meaning of each fit index in your table:

Table No. (2): explain the Baseline Comparisons

Model	NFIDelta1	RFIrho1	IFIDelta2	TLIrho2	CFI
Default model	.792	.765	.824	.800	.823
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

- NFI (Normed Fit Index) assesses the proportion of improvement in fit of the tested model compared to the null model (independent model), The NFI value ranges from 0 to 1, where higher values indicate better fit, Default model NFI: 0.792, Saturated model NFI: 1.000 (perfect fit), Independence model NFI: 0.000 (poor fit)
- Delta1 is a modification index that suggests how much the fit of the model would improve if a particular parameter were added, this index helps identify specific areas for model improvement, Delta1 values are not directly comparable across models.
- RFI (Relative Fit Index) is another index that compares the fit of the tested model to the independence model (null model), Like NFI, RFI values range from 0 to 1, with higher values indicating better fit, Default model RFI: 0.765, Saturated model RFI: Not provided (perfect fit), Independence model RFI: 0.000 (poor fit)
- Rho1 is a relative non-centrality index, which measures the proportion of non-centrality in the model relative to the null model, Rho1 values are not directly comparable across models,
- IFI (Incremental Fit Index): compares the fit of the tested model to the independence model, considering the degrees of freedom, IFI values range

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from 0 to 1, with higher values indicating better fit, Default model IFI: 0.824, Saturated model IFI: 1.000 (perfect fit), Independence model IFI: 0.000 (poor fit)

- Delta2: Similar to Delta1, Delta2 is a modification index suggesting how much the fit of the model would improve if specific parameters were added, Delta2 values are not directly comparable across models.
- TLI (Tucker-Lewis Index) compares the fit of the tested model to the null model, considering the degrees of freedom, TLI values range from 0 to 1, with higher values indicating better fit, Default model TLI: 0.800, Saturated model TLI: Not provided (perfect fit), Independence model TLI: 0.000 (poor fit).
- CFI (Comparative Fit Index) compares the fit of the tested model to the independence model, considering the degrees of freedom, CFI values range from 0 to 1, with higher values indicating better fit, Default model CFI: 0.823, Saturated model CFI: 1.000 (perfect fit).

4.3 Parsimony-Adjusted Measures:

This measure represents "Proportional Reduction in Error." It measures the reduction in error achieved by using the model's predictions compared to the baseline of no prediction (using only the mean of the dependent variable). A PRATIO value close to 1 indicates that the model's predictions significantly reduce the error compared to the baseline, PNFI. This stands for "Parsimonious Normed Fit Index." It evaluates how well the model fits the data while taking into account the model's complexity. A PNFI value closer to 1 indicates a better fit, PCFI This represents "Parsimonious Comparative Fit Index." It measures the model's fit by comparing it to a baseline or comparison model. A higher PCFI value suggests a better fit compared to the baseline model.

PRATIO Default model is 0.886 this indicates that the model's predictions reduced the error by a substantial proportion compared to the baseline, PNFI: 0.701 this suggests that the model fits the data reasonably well, PCFI 0.729 This indicates that the model's fit is relatively good when compared to a reference model.

Table No. (3): show the Parsimony-Adjusted Measures

Model	PRATIO	PNFI	pcfi
Default model	.886	.701	.729
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

4.4 Noncentrality Parameter

NCP: this stands for "Noncentrality Parameter." In statistical hypothesis testing, the noncentrality parameter is a measure of the departure from the null hypothesis. It provides information about the effect size or the strength of the relationship between variables.

LO 90this stands for "Lower Bound of the 90% Confidence Interval." A confidence interval is a range of values within which the true value of a parameter is likely to fall with a certain level of confidence. The lower bound represents the lower limit of this range, HI 90 this stands for "Upper Bound of the 90% Confidence Interval." Similar to the lower bound, the upper bound represents the upper limit of the confidence interval, Here's what the values in the table mean:

The default model (NCP) is 822.781 this indicates the noncentrality parameter for the default model, LO 90 726.942 This is the lower bound of the 90% confidence

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interval for the noncentrality parameter of the default model, HI 90: 926.120 this is the upper bound of the 90% Confidence interval for the noncentrality parameter of the default model.

The Independence model (NCP) 4639.295 this indicates the noncentrality parameter for the independence model, LO 90: 4416.231 (This is the lower bound of the 90% confidence interval for the noncentrality parameter of the independence model, HI 90: 4869.604 (This is the upper bound of the 90% confidence interval for the noncentrality parameter of the independence model.

Table No. (4): shows the Noncentrality Parameter

Model	NCP	LO 90	HI 90
Default model	822.781	726.942	926.120
Saturated model	.000	.000	.000
Independence model	4639.295	4416.231	4869.604

The table No. (5) provided seems to contain descriptive statistics for a variable, specifically related to the variable Production efficiency These statistics provide a summary of the distribution and characteristics of the data for that variable. Let's go through each statistic and what it represents. The mean (average) value of the variable is 3.4002. 95% Confidence Interval for Mean This interval provides a range within which the true population mean is likely to fall with a certain level of confidence (95% in this case). The lower bound of the confidence interval is 3.3075, and the upper bound is 3.4930, 5% Trimmed Mean This is the mean calculated after removing the lowest and highest 5% of the data values. In this case, the trimmed mean is 3.4430, Median: The median is the middle value of the dataset when it's

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sorted. In this case, The median is 3.5000, Variance: Variance measures how much the values in the dataset deviate from the mean. A smaller variance indicates that the data points are closer to the mean. The variance here is 0.948, Standard Deviation: The standard deviation measures the average amount of deviation of each data point from the mean. It's the square root of the variance. Here, the standard deviation is approximately 0.97379, Range: The range is the difference between the maximum and minimum values. Here, the range is 4.00, Interquartile Range: The interquartile range (IQR) is the difference between the first quartile (25th percentile) and the third quartile (75th percentile). It gives a measure of the spread of the middle 50% of the data. In this case, the IQR is 1.00, Skewness: Skewness measures the asymmetry of the distribution. A negative skewness indicates that the distribution is skewed to the left (tail on the left side of the peak). The skewness value is approximately -0.528, with a standard error of 0.118, Kurtosis measures the heaviness of the tails of the distribution compared to a normal distribution. A value of 0 represents the normal distribution. Positive values indicate heaviest tails, while negative values indicate lighter tails. Here, the kurtosis is 0.084, with a standard error of 0.236. These statistics collectively provide insights into the central tendency, spread, shape, and characteristics of the dataset for the variable Kurtosis measures the heaviness of the tails of the distribution compared to a normal distribution. A value of 0 represents the normal distribution. Positive values indicate heaviest tails, while negative values indicate lighter tails. Here, the kurtosis is 0.084, with a standard error of 0.236. These statistics collectively provide insights into the central tendency, spread, shape, and characteristics of the dataset for the variable Kurtosis measures the heaviness of the tails of the distribution compared to a normal distribution. A value of 0 represents the normal distribution. Positive values indicate heaviest tails, while negative values indicate lighter tails. Here, the

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kurtosis is 0.084, with a standard error of 0.236. These statistics collectively provide insights into the central tendency, spread, shape, and characteristics of the dataset for the variable Production efficiency. They help in understanding the distribution of the data and its various properties.

Table No. (5): Descriptions of Variables

		Statistical	Std. Error
Production efficiency	Mean	3.4002	.04718
	95% Confidence Interval for Mean	3.3075	
	Lower Bound	3.4930	
	5% Trimmed Mean	3.4430	
	Median	3.5000	
	Variance	.948	
	Std. Deviation	.97379	
	Range	4.00	
	Interquartile Range	1.00	
	Skewness	-.528-	.118
	Kurtosis	.084	.236

5. Conclusions

In the context of categorical data analysis, as shown in Table No. (1) These models are typically used to assess how well the observed data fit the expected distribution. The p-value indicates the significance of the chi-squared statistic, with smaller p-values suggesting a poorer fit of the model to the data. A lower CMIN/DF ratio generally means a better fit for the model.

The "Default model" represents the model you are testing, The "Saturated model" is the model that perfectly fits the data, as it has as many parameters as there are data points, The "Independence model" is typically used as a baseline model , assuming independence between the variables, to compare against your tested model, the low p-values for both the default and independence models suggest that these models are an improvement over the saturated model, indicating significant that they provide a better fit to the data. The relatively low CMIN/DF ratio in the default model suggests a reasonable fit. The high CMIN/DF ratio in the independence model indicates a poorer fit, which is expected since it assumes independence between variables.

In Table (2) indices fit various perspectives on how well the tested models fit the data. Higher values indicate better fit, and the values are often compared to those of the null (independence) model and a perfect fit (saturated) model. The Default model appears to have an intermediate fit quality between the poor fit of the independence model and the perfect fit of the saturated model.

Table No. (3) Evaluates different models based on their ability to predict error, fit the data, and perform better than reference models. The values provide insights into how well each model performs regarding prediction accuracy and fit to the data.

Table No. (4) Provides information about the noncentrality parameter and its confidence intervals for different models. The noncentrality parameter reflects the effect size or the strength of the relationship being tested, and the confidence intervals provide a range of values within which this parameter is likely to fall.

Recommendations

To increase the accuracy and repeatability of manufacturing processes, should laser enhanced manufacturing techniques be used to manufacture fine production?

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The necessity of modeling and simulating thermodynamics by using robots to withstand high temperatures and extreme cold instead of humans.

The need to use machines that have the ability to analyze liquids and its flow speed, with the activation of the vibration element at the end of the product manufacturing

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