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Artificial intelligence towards a smart automotive supply chain performance KPIs aligned with IATF 16949 standards

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A B S T R A C T

Auto accessories such as car covers provide an added extra in automotive styling both in the look and construction. Any fault in these components will reduce customer satisfaction and result in higher warranty expenses among manufacturers. Automotive sector as per IATF 16949 requirements requires a very effective and strong control of its processes to reduce the defects and enhance productivity. Thus, improved methods for defect identification and higher levels of quality assurance during production are critical issues of current concern. This research focuses on the use of Artificial intelligence (AI) in the automotive industry with an emphasis of using computer vision for superior improvement of quality KPIs. The purpose is to provide an efficient system and organizational approach to the further optimization of the end-of-line inspection of covers for vehicles, and to improve the efficiency of the identification of defects under IATF 16949 regulations. This study is unique in adopting a case based on smart splicing technology implemented in the cutting area of the automobile manufacturing lines. This paper simultaneously applies AI and IoT in order to understand its degree of influence in the definitive performance KPIs. Insignificance may be identified through the application of linear regression used to analyze the correlation between the applied technology and subsequent performance gains. Experimental outcome shows a significant decline on the number of defects that are identified at the last inspection process as well as an improvement on the rate of production. AI particularly contributed to enhancement of inspection processes thereby minimizing non-value adding activities and hence improving overall quality of the products. The current study also encourages manufacturers to adopt intelligent technologies since the AI technologies implemented within the IATF 16949 standards can boost the automotive production quality and decrease the costs and customer dissatisfaction. The automotive industry has changed today due to the implementation of IoT and AI in manufacturing, as this work has shown, with an exciting horizon of the constant automation process and increasing quality indications to deliver on the promise of the redefined definition of success in this industry.

1. Introduction

The automotive industry is undergoing a profound transformation, and evolving rapidly. but still the most important issue to ensure, challenging companies to meet customers' expectations focusing on the three golden criteria of pyramid, produce a product with high quality that respect the standards according to the rigorous requirements of IATF 16949, reducing costs of production and offering the product with a competitive price, without forget to deliver the demand on time. To maintain their competitiveness on the market and keep the loyalty of their customers. Therefore, each company none stop thinking how to provide the automotive requirements, it becomes a must to integrate technology on the company's supply chain putting innovation at the head (Assia et al., 2024), enhancing artificial intelligence (AI), manufacturers will improve their performance

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KPI's with a focus on both operational efficiency and product quality. With the advent of artificial intelligence, automotive industries will transform and optimize their modest supply chains to a smart supply chain by leveraging AI driven solutions, automakers will create an area of production more connected, intelligent responsive to the challenges of tomorrow's vehicles, regarding the manual inspections, which can be time-consuming, inconsistent, and prone to human error.
AI has the potential to revolutionize quality management within automotive supply chains, enabling manufacturers to produce better vehicles while reducing costs and mitigating risks. By harnessing AI for automated inspections and enhanced transparency, automotive companies can build smarter, more resilient supply chains. As AI technologies evolve, the automotive industry will continue to benefit from increased efficiency, improved product quality, and a more sustainable approach to manufacturing. The purpose of this paper is to explore the application of artificial intelligence to enhance performance KPIs in the smart supply chains of the automotive industry, in relation to IATF 16949 standards. It specifically focuses on efficiency and quality KPIs, utilizing computer vision AI tools to identify and eliminate associated wastes. The data analyzed in this research comes from the Cutting Department of an automotive covers company that has recently implemented an intelligent system 'Smart spllicing'.

This research paves the way for broader applications of artificial intelligence in manufacturing, such as automated decision-making processes and smart factories.

2.litterature review

Today AI technologies are a significant trend that all researchers, practitioners, and investors attempt to make it strategic. So that, to achieve and effectively manage a value chain, a research project or a field initiative that meet the various needs of the consumers, customers, and stakeholders regardless of the current environment, it is also relevant to pay a lot of attention to process enhancement and address the issues and concerns. This process seeks to gain the maximum sustainable benefit with the least change and at the same time to cultivate generous error control culture. Several studies and reviews have taken this path to identify, analyze and result in the role of AI for industrial supply chains: Exploratory aspects around the use of data science and machine learning are trending in the facet of customer focus in the automotive industry. It helps to enhance the marketing communication, develop more targeted products, and to give an increased experience for the customer. Over time, this set of technologies will only become more potent in increasing customer satisfaction and developing their loyalty (Hofmann et al., 2017). As such when using the application of machine learning AI tool to predict the Overall equipment effectiveness (OEE), the manufactory was able to record improved productivity, reduce costs and help with excellent decision making. To make the leading organizations be more competitive in the context of the market. Apart from increasing efficiency in operations, automatically integrated solutions provide a basis for further development of inventiveness in the manufacturing industry (Min, 2009). The key AI subfields explored in the context of supply chain management (SCM) include:

1. Expert systems
2. Agent-based systems
3. ANN as one of the artificial intelligence model
4. Machine learning
5. Genetic algorithms (GAs)
6. Fuzzy logic

These sub-fields have also been applied to solve numerous SCM problems including inventory control, procurement, facility location, transportation consolidation and route scheduling challenges as demonstrated (Helo & Hao, 2021). Table 1 displays the impact of using artificial intelligence (AI) in different fields of the supply chain.

Table 1
AI application in the supply chain

Insight of supply Chain	Impact of using AI
Forecasting demand	Integrated into the pack of AI tools, machine-learning algorithms play an essential role in improving demand forecasting by analyzing the historic data and in real time to provide a reduction of errors (Ahmed et al., 2022). This is the rate of prevention and reduction of forecasting errors through the application of predictive models (Carbonneau et al., 2008; Riahi et al., 2021).
Stock optimization	Inventory reduction of up to 20 % - 30% through the application of AI tools (Jamous et al., 2021) to help optimize stocks by adjusting stock levels according to real-time data (Mitta, 2024).
Logistics management	The road to optimized logistics management paved by the application of advanced AI tool technologies that improve the planning and execution of logistics operations (Kitzmann et al., 2023). Richey et al. (2023) and Khare and Srivastava. (2022) have recently shown that AI transforms the supply chain by improving delivery transportation and time of deliveries, moreover the delivery cost management will be reduced (Vanoy, 2023).
Quality and Inspection	Among the benefits of these new AI advanced technology systems is the improvement of quality (Moniz et al., 2022) as a crucial element for smart supply chains in industries (Chouchene et al., 2020) in line with the requirements of IATF 16949. A review has shown that AI helps detect defects with an accuracy of over 90% for products in the automotive sector (Lodhi et al., 2024). Taking as a tool computer vision implemented by AI technology shows that the detection of errors will be up than 95% leading to zero defect (Schulter et al., 2021) and (Konstantinidis et al., 2021).
Predictive Maintenance	The AI technology used to reduce the maintenance costs of industrial machines (Theissler et al., 2021), also known as predictive maintenance, is the key to reducing machine downtime (Arena et al., 2021)
Customized production	The goal of companies is to satisfy their customers while meeting their requirements and needs (Tubaro & Casili, 2019). Through AI, they can better offer customized production solutions (Wan et al., 2020).

3. Methodology

The main objective of this study is to explore the impact of integrating artificial intelligence (AI), in particular computer vision, in optimizing the quality control process of the automotive supply chain, the case of the automotive covers production industry, while complying with IATF 16949 standards. The study focuses specifically on “smart splicing” technology in the field of cutting parts from rolls of textile, leather, artificial leather, etc., as raw materials to improve key performance indicators (KPIs), such as quality and production efficiency, as well as to optimize end-of-line processes in the automotive industry.
This article will discuss a case study carried out in a multinational automotive plant based in Morocco, with a quantitative and comparative study design. The aim of this approach is to analyze and model the impact of smart splicing technology, being a specific technology based on computer vision integrating artificial intelligence, to improve production line performance, more precisely to reduce defects and improve the efficiency of end-of-line inspections.

The samples in our study are the cut parts making up the automotive covers, which represent the heart of the final product or even the entire product without assembly and animation, aiming to remove the incomplete parts for each production run in a model production line in the cutting zone incorporating this technology developed under the name of smart splicing. The data collection was spread over a period of 7 months for 40 samples. These parts are regularly visually inspected as part of the end-of-line inspection. Collecting the data via a computer vision system integrated into the production process within the cutting unit set up in its first “Quilting” phase. This system is configured to enhance manufacturing defects, human error and material variability. The system uses machine learning algorithms, camera and image analysis algorithms to identify material defects, visual analysis for the optimization aspect of mattress alignment, as well as the optimization of raw material utilization through the integration of materials database analysis. Quality indicators (KPIs) such as defect rate, number of incomplete parts, technology usage and smart splicing usage time were recorded. Historical production defect data (prior to AI implementation) were also used for a before-after comparison, as were cycle time and OEE.

The procedure used for our study is as follows:

1. Technology implementation phase: Once the computer vision system had been installed, a period of calibration and validation of the algorithms took place. The system was tested on a dataset of example mattresses with overlap (end of roll and beginning of another roll at the time of the quilting operation), which subsequently creates incomplete pieces in the cutting phase, as well as the misalignment anomaly of the mattress layers. In order to verify its ability to identify anomalies accurately and to find the best optimal solution for cutting the material with the choice of the best cutting parameters according to the specific characteristics of each material to be cut.

2. Data collection: Inspections were carried out continuously during the production of the parts to be assembled. Daily production and incomplete parts were recorded in a database.

3. KPI comparison: The data collected was compared with performance indicators prior to AI implementation. Measures compared included:

o Defect rate of incomplete parts and official claims from other production units having as input the semi-finished product delivered by the autonomous cutting production unit, compared with the IATF 16949 standard.
o The cycle time of the production operation in the cutting zone before and after the implementation of smart splicing.
o Reduced rework costs due to fewer defects, in fact the elimination of major defects of incomplete parts issuing from the cutting APU.

The analysis of the data collected was carried out using several methods, in the following stages:

Step 1: Linear regression: A linear regression model was used to assess the impact of changes resulting from smart splicing technology and computer vision on quality indicators (KPIs) such as the defect rate appearing in the number of incomplete parts as an independent variable, taking into account dependent influencing variables such as technology usage and smart splicing usage time. Regression was used to estimate the effects of changes on production quality and to assess their statistical significance, modeled by visualizing regression diagrams for each variable, and to visualize the interaction between the defect rate dependent variable and the two independent smart splicing variables, we will use a surface diagram, known in statistics as a “response surface diagram”.

Step 2: Significance test: We used statistical tests (such as the Student's t-test) to evaluate significance of observed differences in KPIs.

Step 3: Descriptive analysis: An analytical study described the characteristics of each KPI before and after the introduction of AI. Results were compared to assess changes in production performance.

This study adheres to the ethical standards surrounding the design of real data in industrial fields. Despite the fact that this study does not involve human subjects or experimental animals, confidentiality protocols have been put in place to ensure sensitive production information and compliance with information security standards. This makes it possible to observe the impact of AI on the automotive production chain. Within the framework of an IATF 16949-compliant production system, the application of computer vision offers new opportunities for minimizing defects, improving the quality of finished products and reducing costs. This has led to the development of a robust approach to analyze the impact of integrating this developed smart splicing technology in the improvement of quality processes in automotive production, even for the textile and clothing industries whose production process includes the phase of cutting the raw material into roll form. This also provides a frame of reference; for further research into the integration of AI in Industry 4.0; with particular reference to quality control systems.

3. Choice of AI Tool: Computer vision

The selection of computer vision as an AI tool in the automotive supply chain has major benefits in the optimization of execution and precision (Yousif et al., 2024). Through implementing computer vision technologies, production line quality control is automated, where quality issues are identified early enough (Hussain, 2023). This technology also helps to enhance the inventory control through vision inspection for parts and material for optimal stock control (Yousif et al., 2024). In addition, in handling and tracking vehicles and shipments, computer vision can reduce lying time and hence, improve the transit responsiveness (Riasanow et al., 2017). At the same time, improving the degree of digital transformation in the automotive industry means that tools based on computer vision technology will soon become dominant factors in improving the basic parameters of efficiency and competitiveness (Chinnaiyan et al., 2025).

3.1 Correlation with IATF 16949

Before speaking about a quality management system, it is impossible not to mention standards on which its creation depends. Quality is generally linked with these requirements and norms, particularly; quality in the automotive industry is related with concrete client standards (Ruswanto & Saroso, 2018). There are no exact yardsticks or parameters that can be used to describe a good or a bad system; but a system is as good or as bad as it succeeds or fails to achieve these benchmarks. IATF 16949 is the most used and recognized standard of quality management for the motor industry (Fonesca & Domingues, 2017). Quality management in the automotive sector is an essential activity that requires knowledge, understanding and leadership to fit in. Various fields that have formed industries need to upgrade their awareness and competency in knowledge and Skills (Montenegro, 2020) for now and then in order to be aligned with the modern developments such as Industry 4.0 and artificial intelligence in order to meet IATF 16949 standards (El Affaki et al., 2024) (Singh, 2014). Computer vision is an essential aspect of AI in promoting enhanced quality KPI measurement in automotive supply chain systems (Yousif et al., 2024). The use of this technology assists companies keep IATF 16949 requirements and provide the best quality products. Inasmuch as the industry gets Politicked with smart supply chains, the AI tool will get even more relevant as a driver of quality and effectiveness.

4. Case study: smart splicing in cutting area for covers automotive industries

4.1 Background

In today's demanding and fast-moving automotive industry, a mindset of continuous optimization and improvement has become crucial throughout the supply chain, in order to maintain its weight in this highly competitive market. It is in this context that these emerging automotive markets have undergone a beneficial transformation thanks to the initiation and integration of artificial intelligence (AI) technologies as a strategic response to the challenge of manufacturing products with irreproachable quality while optimizing production time (Rother et al., 2019). Among these innovative tools, the computer vision tool stands out, residing in the application of smart splicing, which sticks out for its potential to improve and optimize the manufacturing process, more specifically the improvement of performance KPIs for industrial excellence (Loch et al., 2003), represented by quality and efficiency. This article explores how the implementation of Smart Splicing can transform these crucial KPIs, particularly in the quilting process for covering automotive industries.

4.2 Smart splicing in the automotive industry

Smart splicing is an advanced technology program that fits in with artificial intelligence tools, as it is a computer vision tool. A multinational automotive company that specializes in producing seat covers for a well-known vehicle manufacturer group developed the operating system of this tool. The production of the covers goes through three main stages, involving three large autonomous production units (UAPs): autonomous cutting production unit, autonomous animation production unit, and the final production stage, autonomous sewing production unit.

Cutting APU: the main intermediate stages of production in this plant are divided into three (quilting, conductor and the last stage, called the preparation phase). The input is raw material in the form of textile rolls, and the semi-finished products in this plant are digits (small pieces of textile) with very specific geometric shapes, developed in the preliminary design stage of the car seat product in the various car projects known to research and development (R & D) phase.

Animation APU: in this phase after getting the digits that are cut in the cutting unit, according to the design of the cover for the car and the targeted projects. If there is a decoration, (zigzag or well-defined aesthetic styles) they must pass secondly to this unit to fulfill this criterion in order to satisfy the predefined need in the customer's specifications.

Sewing APU: This is the last phase of production in this plant of car seat covers located in Morocco. This phase involves combining the prerequisite digits of the two units already mentioned; sewing the digits according to the predefined DT technical file with very precise methods; in order to achieve a better product that complies with all the requirements of the end customer. Either keeping in mind that this stage is 100% manual, production operators who perform the sewing operation on sewing machines, assembly or topstitching.

This AI tool has been developed and implemented in the first part of production in the cutting unit, which has the following sub-steps: quilting, cutting and the last phase preparation of the cut digits. Considering that, this covers multinationals based in Morocco that have suffered from several performance problems in this cutting area, which is the basis of this plant, since the cut parts (digits) are delivered to all the production units that follow it. The minor defect or delay of production, or even stoppage, affect the entire supply chain of this automotive company, which in turn impacts its performance KPIs, notably quality and efficiency, which are not in line with the requirements of IATF 16949, hence the idea and development of an artificial intelligence computer vision tool.

It should be pointed out that this study was based on the implementation of smart splicing technology for one cutting line out of 13 in the plant at the cutting area.

4.3 How the smart splicing works

The Smart splicing is an advanced AI technology for cutting automotive seating, used in the first stage of cutting. Which refers to the quilting phase, whereby a computer connected to the quilting machine integrates software that treats input data transformed into an algorithm. Then this system analyzes the data and results in the best cutting solution, considering that this smart splicing system is synchronized with the cutting section of the lectra machine CNC (Jacob, 2008).Then the quilting process becomes more automated (Dwivedi, 2013) using this advanced smart splicing technology, the table 2 below concretizes the inputs and outputs for this intelligent system:

Table 2
Smart splicing input and output

Input	***<u>Permanent information to fill in</u>*** :(before quilting operation) -Scan of a frozen standard cutting plan; -Scan Galia roll (identification paper); -Scan of the declared number of supplier defects on the Galia roll. ***<u>Information to be added if necessary</u>***:(during quilting operation) -End of roll without having finished the number of layers to be quilted -Presence of a supplier defect at the time of quilting
Output	Suggest the best way to cut, to obtain the exact number required. -Material optimization: Minimize raw material waste; -Absence of incomplete parts ; -Optimize the occupancy rate of the Lectra (the part cut by the CNC machine); -Avoid the errors made by the operator named machine operator, concerning the cutting part of the machine such as entering false information concerning the material to be cut, the number of quilted layers and the parameters for cutting; -Increase machine OEE; -Reduce costs related to re-stripping (recutting operation); -Avoid the problem of overstocking by cutting the exact demand, neither less nor more.

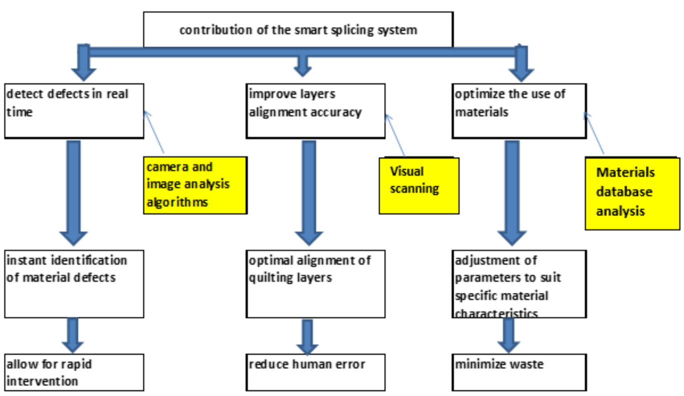


Fig. 1. smart splicing contribution

The main contribution of this technology combining AI and IoT declared in this study include challenges to enhance such as manufacturing defects, human error and material variability, which compromise process efficiency and cost effectiveness, Fig. 1 illustrate the contribution of smart splicing.

4.4 Linear Regression Analysis of Smart Splicing Impact on Performance KPIs

In this part of our article, we try to verify the effect of smart splicing technology on KPIs through linear regression analysis (Yan & Su, 2009). Things become complicated with multiple dimensions, dependent variables or independent variables. Here comes linear regression to the rescue. Linear-regression is a powerful statistical tool reflecting predictive behavior of data (Sedgwick, 2013).

4.4.1 Understanding the Model

The linear regression model expressed as the equation 1 below:

$$y = \beta 0 + \beta 1X1 + \beta 2X2 + \epsilon \tag{1}$$

where :
Y: represents the dependent variable Quality KPI (incompletes parts rate)
β_0: is the y-intercept.
β_1: is the coefficient that indicates the change in Y for a one-unit change in X1 (Use of smart splicing (binary)).
β_2: is the coefficient that indicates the change in Y for a one-unit change in X2 (running time (hours)).
ϵ : epsilon is the error term.

4.4.2 Data Collection and Variables
To effectively analyze the impact of this technology on quality performance KPI, we collected data for 7 months before and after the implementation of smart splicing, based on artificial intelligence, the key variables in our study are:

- Dependent Variables: Quality KPI defect rate (in our case incomplete parts rate) calculated with the equation 2 below.

$$Y_i\ (\%) = \frac{A_i}{B_i} * 100 \tag{2}$$

where :

Y: represents the dependent variable Quality KPI (incompletes parts rate).
A: is the number of incompletes parts.
B: is the total number of produced parts.
i : represents defined period of time (in this case study in an average of two days and two shifts).

- Independent Variable: The extent of smart splicing adoption, measured through metrics such as: -use of smart splicing binary (1 the technology is used in production, 0 the technology is not used while producing)

-running time (hours): represents the time during which the system is in active operation (in our case, the running time is displayed directly on the system screen, with no need to calculate it manually).

Table 3 below contains all the data required in 7 months for a sample size of 40 to perform the linear regression after implementing the smart splicing tool at the quilting stage of the raw material cutting unit.
For the first few months, the new smart splicing technology was used for a few hours of operators training by an expert.

Table 3
Sampling data after smart splicing implementation

Samples	*Quality KPI (incompletes parts rate)*	*Use of smart splicing (binary)*	*running time (hours)*	*Frequency*
1	8.90%	0	2	1st month
2	8.70%	0	3	
3	8.90%	0	2	
4	8.20%	0	4	
5	7.50%	0	3	
6	7.80%	0	4	2nd month
7	7.40%	0	3	
8	7.20%	0	3	
9	7%	1	4	
10	7%	0	4	
11	6.90%	0	8	

Table 3
Sampling data after smart splicing implementation

Samples	*Quality KPI (incompletes parts rate)*	*Use of smart splicing (binary)*	*running time (hours)*	*Frequency*
12	7.00%	0	3	3rd month
13	7.00%	0	2	
14	6.98%	1	10	
15	6.98%	1	16	
16	6.90%	1	14	
17	6.79%	1	10	
18	6.92%	0	5	4th month
19	6.72%	1	14	
20	6.70%	1	18	
21	6.64%	0	6	
22	6.62%	1	12	
23	6.59%	1	12	
24	6.56%	1	12	5th month
25	6.50%	0	7	
26	6.60%	1	13	
27	5.10%	1	20	
28	4.20%	1	20	
29	3.90%	1	28	
30	3.20%	1	24	6th month
31	2.90%	1	21	
32	2.30%	1	25	
33	2.00%	1	21	
34	1.80%	1	22	
35	1.50%	1	26	
36	1.01%	1	27	7th month
37	1.00%	1	24	
38	0.80%	1	28	
39	0.68%	1	28	
40	0.60%	1	30	

4.4.3 Results and Interpretation

Table 3 below provides a detailed report on our regression, to analyze the impact of smart splicing on Quality KPI for automotive companies seeking a smart supply chain.

Table 3
regression statistics

Regression statistics	
Multiple coefficients of determination	0.92621401
Coefficient of determination R^2	0.8578724
Coefficient of determination R^2	0.85018982
Standard error	0.01010275
Observations	40

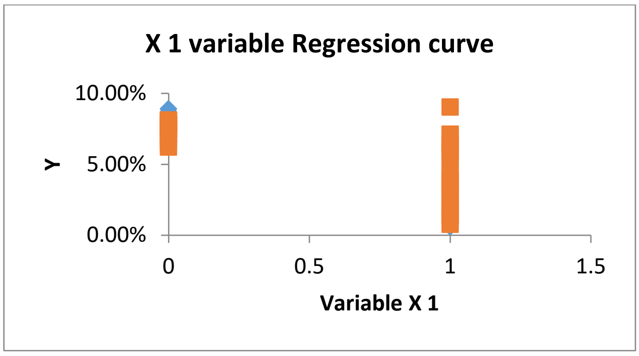
VARIANCE ANALYSIS

	Degree of freedom	*Sum of squares*	*Average of squares*	*F*	*Critical value of F*
Regression	2	0.0203856	0.0101928	97.260189	3.0527E-15
Residuals	36	0.00377277	0.0001048		
Total	38	0.02415837			

	Coefficients	*Standard error*	*Statistics t*	*Probability*	*Lower limit for confidence level = 95%.*	*Upper limit for confidence level = 95%*	*Lower limit for confidence level = 95%.*	*Upper limit for confidence level = 95%*
Constant	0.08751948	0.00283889	30.8287508	5.4485E-28	0.08176734	0.09327162	0.08176734	0.09327162
Variable X 1	0.01544238	0.00544917	2.83389497	0.00740477	0.00440131	0.02648345	0.00440131	0.02648345
Variable X 2	-0.00317275	0.00028481	-11.1400412	2.2323E-13	-0.00374982	-0.00259568	-0.00374982	-0.00259568

The results of this regression analysis indicate a significant relationship between the adoption of smart splicing and improvements in performance KPIs. A positive coefficient 0.015 for the independent variable X1 (use of smart splicing) suggests that increased use of smart splicing correlates with enhanced KPI performance, also negative coefficient -0.0032 for the independent variable X2 (running time) suggests that longer running times linked to better performance (reduced defects).

Providing valuable insights into the effectiveness of this technology. Moreover, the Coefficient of determination R^2 of 0.85 means that 85% of the variation in the dependent variable can be explained by the independents variables in our regression model. In other words, the model fits the data well. This indicates a strong correlation, Fig. 2 and Fig. 3 show the regression curve for each independent variable interacted on the defect rate as a dependent variable:



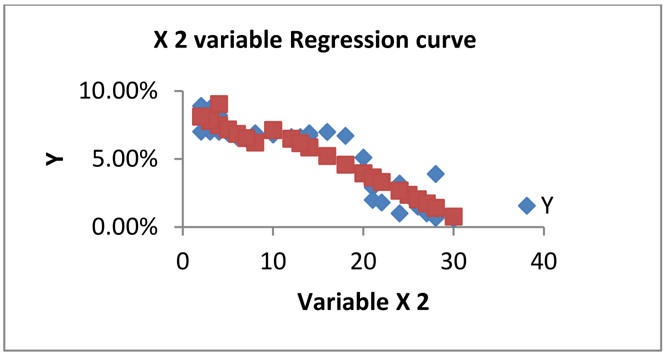


Fig. 2. use of smart splicing regression curve

Fig. 3. Running time of smart splicing regression curve

In order to model and visualize the interaction between the defect rate dependent variable and the two independent smart splicing variables, we will use a surface diagram, known in statistics as a “response surface diagram” or “response surface”) (He et al., 2024), as shown in the figure below:

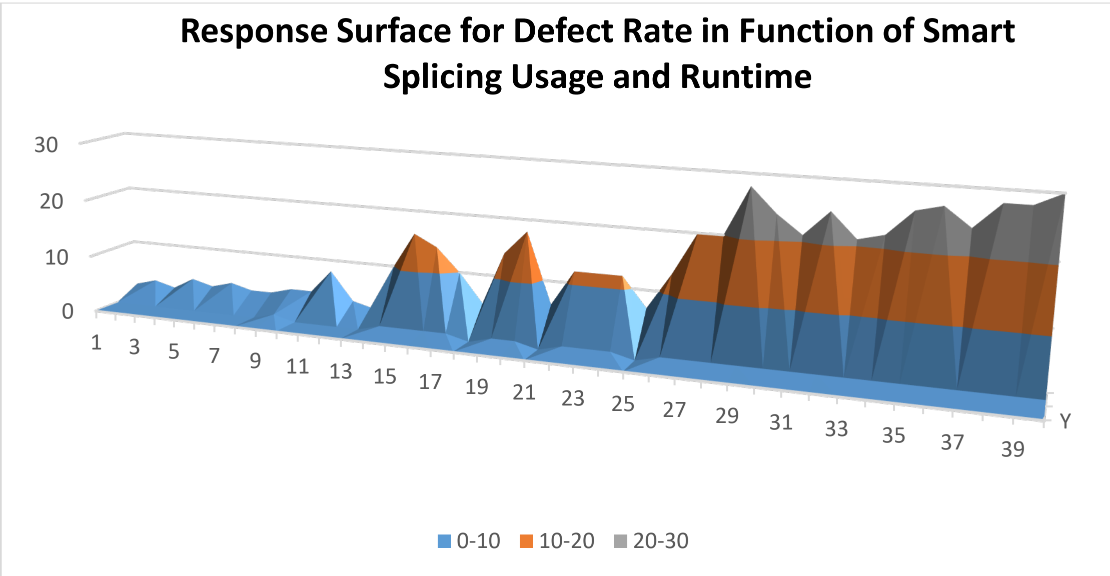


Fig. 4. Response Surface for defect rate

Linear regression is in summation, a strong mechanism by which smart splicing and its impact on gamified performance metrics can be understood quantitatively. Not only does this analysis show the advantages of including AI technologies, but it also serves to help organizations make data-driven decisions as per their inclusion.

4.5 Impact on quality KPIs

4.5.1. Reducing defect rates

When we talk about defects affecting this production unit of cutting UAP, we need to focus on the major defect:

Incomplete parts that escape during the preparation phase of cutting area and arrive at the internal customers, who are production lines assembling the cut parts sewing UAP, even these defects can escape from the production plant and arrive at the end customer with covers that are incorrectly assembled because of the first non-conformity issue.

This defect is found with the problem of covering operation; (At the time of quilting if the roll is finished, we must start another roll to complete the layer. Alternatively, if there is a marked supplier defect and the operator must remove it by cutting this piece of textile and then continue the operation; nicknamed by the operation of covering ;), pieces that are to be cut in this part will be incomplete. While with the application of smart splicing, we conclude that the problem is well resolved with a percentage of 100%, no more incomplete pieces due to covering operation. Before the implementation of this intelligent technology, an exponential trend that was for the defect rate for incomplete parts measured by two indicators followed in cutting UAP: number of incomplete parts during the final control in the preparation phase at the cutting area and the indicator of the number of internal complaints from other assembling UAPs depending on incompletes parts. The use of computer vision allows it to bring it back to 0%, thus guaranteeing a production in accordance with high quality standards focusing on the automotive standard IATF 16949, Fig. 5 and Fig. 6 below show the trend.

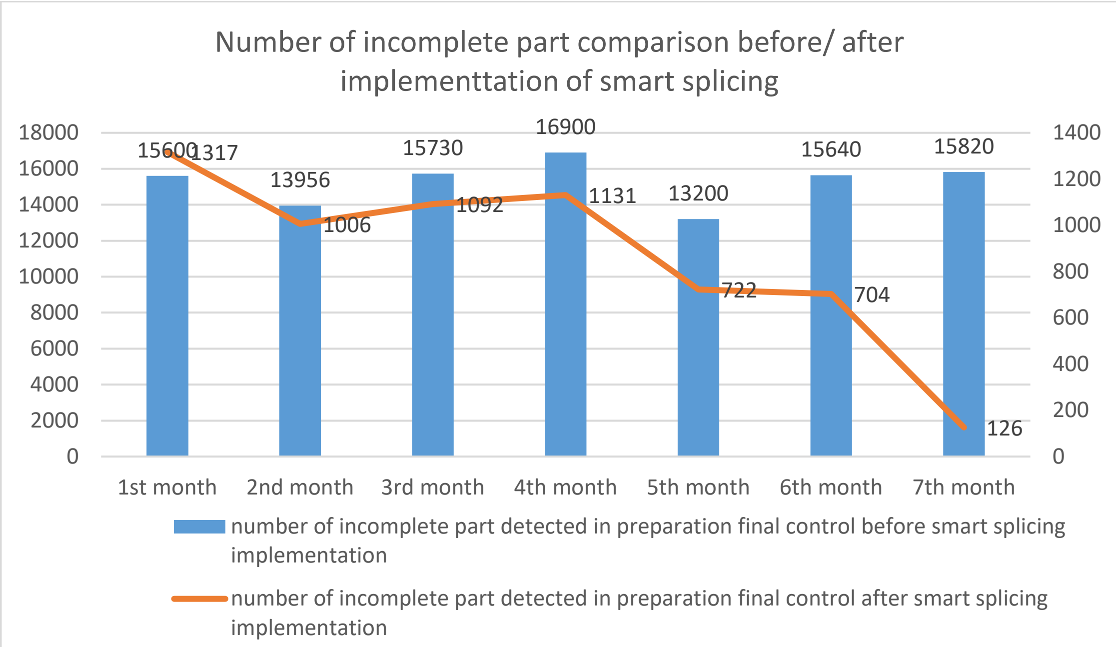


Fig. 5. Before / after comparison number of incomplete part

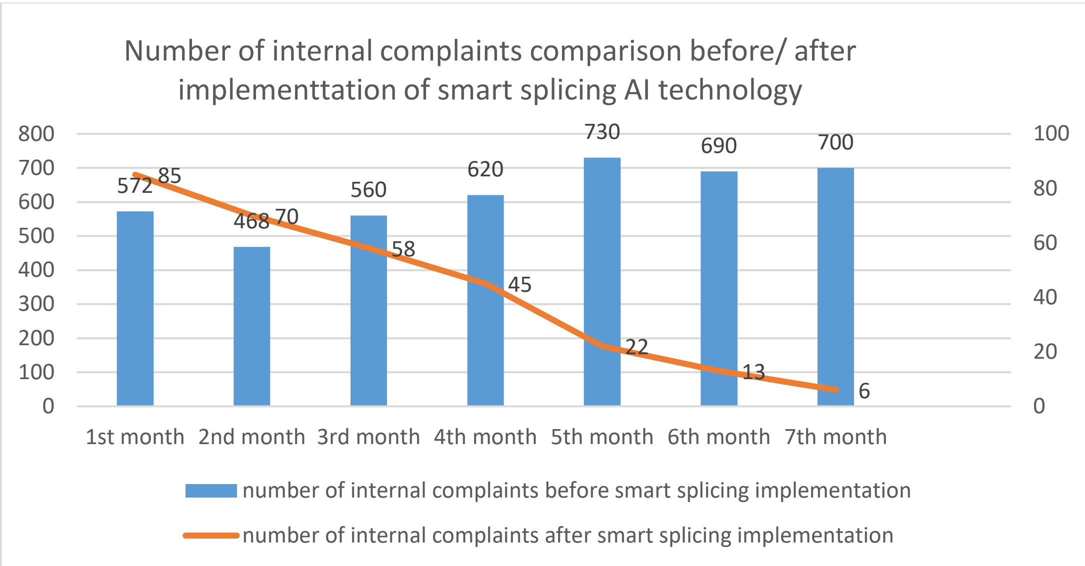


Fig. 6. Before / after comparison number of internal complaints

4.5.2. Improved compliance

This article provides a deep analysis, taking the case of an incomplete part arriving at the customer line or at the preparation phase in cutting UAP, it automatically results in a restriping operation (recut of incomplete parts), which means rework in this industry subject of our article. This article shows that the smart splicing technology has made it possible to achieve the vision of zero incomplete parts. This leads to higher quality and lower rework costs, or even eliminates rework related to incomplete parts caused by recovering operation.

4.6 Impact on efficiency KPIs

4.6.1 Cycle time reduction

Before the smart splicing implementation, the cycle time from the quilting cutting operation through the cutting phase to the final phase preparation was too long, due to manual inspection operations to remove incomplete pieces. As well as the cutting phase's cycle time, which was affected by the machine's set-up step according to the material to be cut, not forgetting the realignment operation in the event of layers deviation in the quilting phase, which must be corrected in this step.
Thanks to the optimization provided by Smart Splicing, these two operations are automated and the problem is solved: cycle times are reduced from 35 to 15 minutes for a standard cutting plan, thus increasing production capacity.

4.6.2 Increase overall equipment effectiveness (OEE)

This research shows that the OEE, which was initially around 65% to 75% for this production line subject to the implementation of this new intelligent technology in cutting area for automotive covers company, was able to reach 85% with the integration of Smart Splicing, by improving the compliance rate and increasing production capacity, which reflects a significant improvement in productivity.

5. Discussion

The results demonstrate markedly better quality KPIs and fewer manufacturing faults with more accuracy in attaining specifications. Otherwise, computer vision has also decreased manual inspection downtime and allowed production lines to run overall smoother. The company realized better compliance with IATF 16949 requirements, especially regarding minimization of production variability and improving process control for defect prevention, after implementing this AI solution. This is where computer vision proves to be that nice, big lever we can pull on the continuous improvement approach that these standards put in place. In the complex field of supply chain management, one crucial link is to have consistent quality products or services delivered. Therefore, what a quality control solution can do is predict and solve problems along the value chain of a company, which will improve customer satisfaction.

5.1 Challenges and opportunities

Integrating computer vision presents a number of challenges, including initial investment in technology and training staff to use automated systems, the table below shows different challenges confronting AI tools.

Table 3
AI technology challenges

System complexity	The AI complexity system cause many problems such as integration issue with existing infrastructure (Smith, 2023) that become a necessity to have a robust architecture in order to support.
Resistance to change	For each change we can see the resistance of collaborators for new technologies this the same issue for AI technologies integration (Ramadhani et al., 2024).
Data Security	The organizations exposed to cybersecurity risk with the increased use of data to AI database (Palle and Kathala, 2024).

Nonetheless, the challenges involved in the realization of this aspect of quality control and meeting the standards are easily outweighed by the long-term benefits in terms of quality of the final product. Moreover, when product quality is maximized, firms are able to contain their cost of returns and warranty repair.

5.2 largeness and ongoing enhancement

Computer vision can be scalable. Over time, the algorithms get refined, and the control almost gets infinitesimally smaller. These features allow developing the quality processes continuously and preserve the compliance to the IATF 16949 requirements.

6. Conclusion & Recommendations for future research

The application of artificial intelligence tools including computer vision; more specifically, smart splicing technology is a strategic development for intelligent supply chains in the automotive industry that explains how the adoption of smart splicing technology improves key performance indicators (KPIs) concerning quality. This technological integration, in accordance with IATF 16949 standards, can significantly improve overall automotive company performance in relation to efficiency and decrease in process variation as well as sustained compliance with the quality standards. The best tools in quality control processes are thus those that support automated quality checks and real-time examinations of production flows, reducing human factors that may result in inefficient use of available resources. Advanced splicing technologies act as intelligent beings and utilize AI strengths in analyzing many datasets and joining them. Using AI, this kind of data analysis provides early signal of defects and real-time decision making which is vital in achieving high quality in the manufacturing line.

Further, the logical application of linear regression analysis used in this article makes it easy to measure the degree of quality performance improvement resulting from integration smart splicing. This model shows how AI works in the production process while giving organizations concrete steps in which action can be taken based on data analytics for increasing efficiency and reducing costs continuously. In this regard the transition to using computer vision and some other AI tools in the automotive industry does not mean enhancing the existing processes only. It stands as a strategic capital to innovation and digitization from which organizations intend to leverage technological disruptions. This constant need to innovate means that a capacity to modify processes constantly by means of AI-based technologies can be a decisive factor in retaining an edge in markets that are now growing rapidly and becoming more challenging. These technologies also assist the companies to better address the IATF 16949 requirements through improved traceability and real-time documentation, therefore constant compliance without exposing companies to non-compliance risks. As more advancements arise in the field of artificial intelligence, computer vision, and data analytics technologies, the automotive industry is moving toward the future where automation, predictions, and self-learning are essential parts of car making.

In the short term, the experience suggests that the use of AI is going to be more and more used, with a greater depth of machine learning, deep learning. These technologies will evolve to resolve other emergent problems like controlling process variability, quality of the articles in process and finished product, with an enhanced degree of automation in future. In the medium term, a new predictive analytics tool based on data collected using AI will enable preventing failure. Together with the mentioned technologies, automotive companies are able to improve the production process and achieve reduced rates of equipment failures and thus prolong the life cycle of the used machinery. In addition, AI solutions applied to the supply change management and inventory control yield new roles in how organizations order and how logistics sources and realigns with the market.

In extending the outlook of intelligent supply chains in the automotive industry, it is envisaged that there might be more expansion of application of block chain to address issues of data security and accuracy. The integration of AI and blockchain has the potential to create full openness and improve tracking throughout the end-to-end production process from the creation of a product, to the examination of its authenticity and quality control right through to delivery of the product. It will also ensure that data exchanges were protected while at the same time creating confidence amongst the stakeholders in the chain. Moreover, possibilities of using AI in the automotive industry demonstrated the potential of getting more bonuses than only better performance and quality. It could further act as an important stakeholder in the creation of effective and lasting change in the direction and management of the industry containing more sustainable principles in the utilization of resources, the reduction of carbon objectives, and providing for a framework that supports the adoption of circular economy practices across the multitudes of organizations within the industry. Businesses might adopt intelligent systems for material flows to control proportions or usage, recycle, and optimize production with regard for sustainability.

Added to that, there is another significant field of evolution: the interaction between AI and employees. Although over the years many aspects of operation could be fully automated and handled by smart systems, the notion of human and automated cooperation will occur differently. Ongoing training and development will be required to facilitate easy change and to guarantee that organizational members are ready to grow with such innovations. Last but not least, cybersecurity and data protection are the issues that will be important in the future. Business people will have to incorporate sophisticated security frameworks over their businesses just to shield their inventions, intellectual properties as well as to retain the confidence of their associates and clients.

All in all, the implementation of AI technologies like computer vision and smart splicing into intelligent supply chains of the automotive industry is not just fulfilling the delivery of short-term capabilities and enhanced quality. It is a change of direction that will set the scene for profound transformations of the entire sector to equip the companies to meet the next challenges in innovation, sustainability and competitiveness.

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