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Implementation of Artificial Intelligence and Robotics in Chennai Automotive Common Facility Centre

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Abstract: The Chennai Automotive Common Facility Centre (CFC) in Tirumudivakkam, Chennai, is a groundbreaking initiative aimed at empowering automotive component manufacturers, particularly Micro, Small, and Medium Enterprises (MSMEs). The objective is to study the Common Facility Centre using 5 point scale and find value description on AI and Robotics implementation before and after cluster development approach at Chennai Automotive Components Industrial Cluster at Tirumudivakkam. The methodology adopted is study on 40 Automotive Components Manufacturers at Tirumudivakkam, Chennai using statistical techniques such as the T-test, Discriminant Analysis and Structural Equation Modelling, The research measures the improvements in production performance driven by AI and robotics integration. The T-test is applied to assess changes in key performance metrics, before and after the cluster development approach. The Discriminant Analysis method identifies the key factors influencing the success of AI and robotics in smart production. Results indicate that the integration of AI and robotics leads to substantial improvements in production effectiveness. Businesses in the cluster experience stronger competitiveness, higher customer satisfaction, and reduced operational costs after adopting these technologies. By leveraging Artificial Intelligence (AI) and robotics, the CFC seeks to drive innovation, enhance operational efficiency, and improve global competitiveness. The facility will provide access to advanced technologies, support end-to-end project development, facilitate the production of higher value-added products, and meet stringent testing standards. It is anticipated to boost cluster turnover by 10%-15%, reduce operational costs, generate employment opportunities, and enhance workforce skills through specialized training programs. Furthermore, the CFC will promote collaboration through shared infrastructure, joint marketing, and collective raw material procurement. With a focus on sustainable growth and economic development, the CFC is set to become a benchmark for industrial excellence and global market integration. To conclude, the adoption of AI and robotics through a cluster development approach offers significant benefits to the automotive components industry in Chennai. This study provides practical insights and recommendations for companies seeking to leverage these technologies to optimize production strategies, enhance operational efficiency, and secure a competitive advantage in the global market.

Keywords: Chennai Automotive Common Facility Centre (CFC), Artificial Intelligence (AI), robotics, Micro, Small, and Medium Enterprises (MSMEs), innovation, global competitiveness, advanced technologies, operational efficiency, value-added products, testing standards, workforce skill development, collaboration, shared infrastructure, joint marketing, raw material procurement, sustainability, economic growth, industrial excellence.

I. INTRODUCTION

Integrating **Artificial Intelligence (AI)** and **Robotics** into the Chennai Automotive Common Facility Centre (CFC) is a game-changing initiative for Automotive Components Manufacturing Enterprises (ACME) in Tirumudivakkam, Chennai region. This move aims to enhance productivity, competitiveness, and innovation while driving economic growth and creating new opportunities for stakeholders.

[1]. **Key Benefits for ACME**

1. **Enhanced Competitiveness**
   - **AI-driven innovation**: Enable the design and development of globally competitive products by analyzing trends and customer needs.
   - **Robotics integration**: Boost manufacturing precision, efficiency, and quality to meet international standards.

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2. **Support for End-to-End Processes**
    - **AI-based prototyping and testing**: Accelerate product development cycles with automated simulations and performance analytics.
    - **Robotic production lines**: Streamline workflows from concept to large-scale production.
3. **Access to Advanced Technologies**
    - **Predictive maintenance**: Leverage AI to monitor equipment health and minimize downtime.
    - **Robotic testing systems**: Provide cutting-edge facilities for testing automotive components, ensuring compliance with stringent quality standards.
4. **Job Creation and Skill Development**
    - **Skill enhancement programs**: Equip workers with expertise in AI and robotic operations through structured training sessions.
    - **Collaborative robotics (cobots)**: Facilitate human-robot cooperation, improving productivity while maintaining job security.
5. **Development of Value-Added Products**
    - Use AI for material and process optimization to create high-value, customized products.
    - Deploy robotics for advanced manufacturing tasks requiring superior accuracy and consistency.
6. **Improved Testing Capabilities**
    - **AI-powered quality control**: Ensure rapid and precise inspection of components.
    - **Robotics in stress testing**: Enhance the reliability and safety of automotive parts through advanced testing protocols.
7. **Operational Synergies**
    - **AI-enabled supply chain management**: Streamline raw material procurement to reduce costs and improve efficiency.
    - Foster collaboration among MSMEs through shared resources, joint marketing initiatives, and common facilities.
8. **Cost Reduction and Revenue Growth**
    - Lower operational and service costs with robotic automation of repetitive and high-labor tasks.
    - Optimize resource utilization with AI, achieving a projected **10%-15% increase in turnover** for MSMEs.

[2]. **Strategic Steps for Implementation**

1. **Infrastructure Development**
    - Establish cutting-edge facilities equipped with AI-driven production and testing systems.
    - Introduce robotics for assembly, welding, painting, and inspection processes.
2. **Technology Integration**
    - Deploy **IoT-enabled devices** for real-time data collection and analysis.
    - Seamlessly integrate AI and robotics with existing production workflows.
3. **Skill Development Programs**
    - Organize training workshops and certification courses on AI and robotics for MSME employees.
    - Collaborate with educational institutions and technology providers to ensure continuous skill upgrades.
4. **Promoting Collaboration and Synergy**
    - Create a digital platform for MSMEs to share insights, access advanced tools, and foster partnerships.
    - Encourage joint ventures in R&D, raw material procurement, and global marketing efforts.
5. **Continuous Monitoring and Optimization**
    - Use AI analytics to monitor key performance indicators, ensuring goals are met.
    - Continuously refine operations through real-time feedback and data-driven insights.

[3]. **Anticipated Impact**

- **Increased global market access**: Help MSMEs compete effectively with innovative, high-quality products.
- **Higher productivity and profitability**: Improved efficiency and reduced operational costs lead to sustainable growth.
- **Skill enhancement and job creation**: Empower the workforce with advanced technical expertise, creating new employment opportunities.
- **Stronger collaboration**: Foster a unified ecosystem among MSMEs, promoting shared success.

By leveraging AI and robotics, the Chennai Automotive CFC will drive a transformative change for MSMEs, making them more competitive, efficient, and future-ready.

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II. LITERATURE SURVEY

The application of **Artificial Intelligence (AI)** and **Robotics** in **Common Facility Centres (CFCs)** has been widely studied to evaluate its potential in improving productivity, reducing costs, and enhancing competitiveness. This literature survey explores key research findings and their relevance to the development of CFCs, especially for **ACME** at Tirumudivakkam, Chennai.

- **1. The Role of AI and Robotics in Manufacturing**
  - **Study**: *Artificial Intelligence in Smart Manufacturing: A Systematic Review* (Zhou et al., 2021)
    - **Key Insights**:
      - AI enhances production scheduling, supply chain management, and resource optimization.
      - Robotics improves precision, consistency, and cycle time in manufacturing.
      - Together, AI and robotics enable predictive maintenance and fault detection.
    - **Relevance**: Demonstrates how AI and robotics can improve operational efficiency in MSMEs through CFCs.
  - **Study**: *Impact of Robotics on Productivity in Small and Medium Enterprises* (Welford et al., 2020)
    - **Key Insights**:
      - Collaborative robots (cobots) are ideal for MSMEs, offering flexibility and cost-effectiveness.
      - Shared access to robotic technologies in CFCs lowers adoption costs for smaller enterprises.

- **2. Benefits of CFCs for MSMEs**
  - **Study**: *Collaborative Frameworks for MSMEs: Pathways to Competitiveness* (Gupta & Sharma, 2019)
    - **Key Insights**:
      - CFCs provide access to advanced equipment and technologies, reducing individual capital expenditures.
      - Shared facilities enhance economies of scale, fostering innovation and collaboration.
    - **Relevance**: Highlights the importance of CFCs as a bridge for MSMEs to access cutting-edge technology.
  - **Study**: *Technology Adoption in MSME Clusters: A Case Analysis* (Bose et al., 2018)
    - **Key Insights**:
      - Common access to AI-enabled tools through CFCs reduced production costs by 15%-20%.
      - Advanced testing facilities in CFCs significantly improved product marketability and readiness.

- **3. Workforce Development and Skill Enhancement**
  - **Study**: *AI-Driven Skill Development in Manufacturing* (Chen et al., 2020)
    - **Key Insights**:
      - AI-based training programs improve worker proficiency in operating advanced systems.
      - Collaborative robots (cobots) enhance worker engagement by simplifying complex tasks.
    - **Relevance**: Emphasizes the role of CFCs in providing skill development programs for MSME employees.
  - **Study**: *Upskilling for the Robotics Era: Challenges and Opportunities* (Mehta, 2017)
    - **Key Insights**:
      - Robotics adoption creates demand for new roles, such as robotic technicians and AI analysts.
      - Establishing training centers within CFCs leads to a more adaptive and skilled workforce.
- **4. Challenges in AI and Robotics Adoption**
  - **Study**: *Barriers to AI Implementation in MSMEs* (Raj et al., 2021)
    - **Key Insights**:
      - Key challenges include high initial costs, limited technical expertise, and resistance to change.
      - Recommended solutions: shared infrastructure, subsidized training, and government incentives.
    - **Relevance**: Highlights the need for a collaborative approach to mitigate adoption challenges in CFCs.
  - **Study**: *Integrating Robotics in MSME Clusters: An Empirical Study* (Singh et al., 2019)

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- **Key Insights**:
  - A phased approach to robotics adoption minimizes operational disruptions.
  - Modular, low-cost robotic systems are more suitable for MSME clusters.

- **5. Success Stories and Case Studies**
  - **Case Study**: *Robotics Adoption in Automotive Manufacturing: Pune Cluster* (Kumar et al., 2020)
    - **Insights**: Robotics implementation in a shared facility increased productivity by 25% and reduced defect rates by 30%.
  - **Case Study**: *AI and Robotics in Germany's Mittelstand Enterprises* (Schneider, 2018)
    - **Insights**: Shared AI-driven facilities helped medium-sized enterprises cut costs and expand into new markets, achieving global competitiveness.

- **6. Key Impacts of AI and Robotics in CFCs**
  - **Productivity Gains**: Robotics and AI reduce manual intervention, minimize errors, and enhance efficiency.
  - **Cost Reduction**: Shared access to advanced tools lowers operational costs for individual MSMEs.
  - **Job Creation**: Robotics integration creates demand for skilled labor in programming, maintenance, and analytics.
  - **Skill Enhancement**: Training programs in AI and robotics upskill workers, improving adaptability and employability.
  - **Market Expansion**: MSMEs gain access to technologies enabling them to meet global quality standards.
  - **Conclusion**

The literature supports the transformative potential of integrating AI and robotics in CFCs. By providing shared access to advanced technologies, fostering workforce skill development, and addressing barriers to adoption, CFCs can empower MSMEs to achieve higher productivity, lower costs, and greater global competitiveness. A well-structured implementation plan, backed by government support and stakeholder collaboration, is essential to realize these benefits in the Chennai Automotive CFC.

Objective of the Study

The objectives are as follows:

To study on the implementation on AI and Robotics in CFC,, before and after cluster development approach at Chennai Automotive Components Industrial Cluster at Tirumudivakkam.

To study on the 5 point scale on implementaion of AI and Robotics in CFC before and after cluster development approach at Chennai Automotive Components Industrial Cluster at Tirumudivakkam.

To study on the best value description on AI and Robotics implementation before and after cluster development approach at Chennai Automotive Components Industrial Cluster at Tirumudivakkam.

By addressing these objectives, the study aims to empower Chennai's automotive component manufacturers to harness the transformative potential of AI and robotics, enabling them to thrive in an increasingly competitive and technology-driven global market.

III. MATERIALS AND METHODS

This study employs a structured methodology to investigate the integration of Artificial Intelligence (AI) and robotics for smart production using 5 point likert scale of primary data in 40 Chennai's automotive components manufactures at Tirumudivakkam, Chennai in industrial clusters using T-test, Discriminant Analysis and Structural Equation Modelling by identifying Problem and Scope by identifying key production challenges and opportunities in Chennai's automotive clusters. The approach is by conducting initial research using secondary data like industry reports, academic literature, and consultations with stakeholders to outline the current state of production practices and technological readiness. The input, process and output variables as per table 1, are analysed and their performance values are found. The data were analysed using T-Test, Discriminant Analysis for before [b] (G=0) and after[a] (G=1) Cluster Development Approach using 10 Predictor Variables for 40 automotive components manufactures at Chennai and also using Structural Equation Modelling.

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Table 1: Visualization of the Conceptual Framework Model

Input variables- Critical gaps identified	**Symbol**	**Process Variables CFC / Intervention**	**Output variables The setting up of the CFC will accrue the following benefits for Automotive Components Manufacturers in the Tirumudivakkam, Chennai**	**Symbol**
Absence of or limited automation in the manufacturing process	La	Design Software	Improving the competitiveness through development of innovative products for global market	Ic
Lack of Standardization	Ls	Manufacturing Machines	Supporting MSMEs from concept to commissioning	Sc
Design and develop new products in the emerging areas	Dn	Design Software	Access to advanced technologies to secure larger contracts at better margins	At
Low capacity and lack of capability	Lc	Manufacturing Machines	The CFC will generate more job opportunities at both the cluster and individual unit level due to the enhancement of capacity utilization.	Jo
Need for re-design to mitigate obsolescence	Rd	Design Software	Support to develop higher value-added products	Va
Absence of testing laboratory nearby	Ta	Testing Equipments	Cater to the advanced testing requirements	Ar
Lack of availability of skilled workers	Sw	Skill Training	The CFC is also expected to enhance the levels of skill of workers throgh skill training	St
Hit and trial method is used to get final product which results in wastage of raw material, money and time and in addition affects their competitiveness in the market.	Wr	Manufacturing Machines	The CFC is also expected to enhance the levels of cooperation and synergy amongst the stakeholders through common raw material procurement & joint marketing initiatives	Rm
Private players charge exorbitant price for their services like testing, machining etc	Pe	Manufacturing Machines	Substantial reduction in operational costs and service costs & CFC could help the industries in the cluster to achieve higher turnover (i.e., 10%-15% higher than usual turnover).	Oc

Source: Created by Researcher

$Op = C + \sum_{I=1}^{8} \beta i\, Xii$ …… [1]

$Op = C + \beta 1\, Ic + \beta 2\, Sc + \beta 3\, At + \beta 4\, Jo + \beta 5\, Va + \beta 6\, Ar + \beta 7\, St + \beta 8\, Rm + \beta 9\, Oc$ …… [2]

Where Op is ouput performance and C is constant and β1, β2… are coefficients.

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IV. RESULTS AND DISCUSSION

T-Test

Table 2: Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Ica	4.00	40	.816	.129
	Icb	2.05	40	.815	.129
Pair 2	Sca	4.00	40	.816	.129
	Scb	2.00	40	.751	.119
Pair 3	Ata	3.98	40	.832	.131
	Atb	2.13	40	.723	.114
Pair 4	Joa	3.95	40	.876	.138
	Job	2.03	40	.698	.110
Pair 5	Vaa	3.93	40	.797	.126
	Vab	2.00	40	.716	.113
Pair 6	Ara	3.85	40	.864	.137
	Arb	2.05	40	.677	.107
Pair 7	Sta	3.83	40	.903	.143
	Stb	2.23	40	.768	.121
Pair 8	Rma	3.85	40	.893	.141
	Rmb	2.03	40	.660	.104
Pair 9	Oca	3.88	40	.883	.140
	Ocb	1.98	40	.660	.104

Source: Computed Data

The mean as given in table 2, after cluster development approach is higher than before cluster development approach which reveals that the automotive components manufacturers used the marketing technologies effectively

Table 3: Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	Ica & Icb	40	.694	.000
Pair 2	Sca & Scb	40	.753	.000
Pair 3	Ata & Atb	40	.560	.000
Pair 4	Joa & Job	40	.632	.000
Pair 5	Vaa & Vab	40	.674	.000
Pair 6	Ara & Arb	40	.670	.000
Pair 7	Sta & Stb	40	.317	.046
Pair 8	Rma & Rmb	40	.659	.000
Pair 9	Oca & Ocb	40	.655	.000

Source: Computed Data

As per table Pair 7is not significant and needs improvement

Table 4: Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Ica - Icb	1.950	.639	.101	1.746	2.154	19.315	39	.000
Pair 2	Sca - Scb	2.000	.555	.088	1.823	2.177	22.804	39	.000
Pair 3	Ata - Atb	1.850	.736	.116	1.615	2.085	15.907	39	.000

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Pair 4	Joa - Job	1.925	.694	.110	1.703	2.147	17.547	39	.000
Pair 5	Vaa - Vab	1.925	.616	.097	1.728	2.122	19.780	39	.000
Pair 6	Ara - Arb	1.800	.648	.103	1.593	2.007	17.555	39	.000
Pair 7	Sta - Stb	1.600	.982	.155	1.286	1.914	10.306	39	.000
Pair 8	Rma - Rmb	1.825	.675	.107	1.609	2.041	17.097	39	.000
Pair 9	Oca - Ocb	1.900	.672	.106	1.685	2.115	17.888	39	.000

Source: Computed Data

There is significant increase in performance after Cluster Development Approach when compared to before cluster development approach on marketing technologies as given in table 4.

Discriminant Analysis

Table 5: Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		80	100.0
Excluded	Missing or out-of-range group codes	0	.0
	At least one missing discriminating variable	0	.0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	.0
	Total	0	.0
Total		80	100.0

Source: Computed Data

In discriminant analysis, the Analysis Case Processing Summary as per table 5, provides an overview of the dataset used in the analysis, detailing the number of cases (observations) that were included, excluded, or missing data. This summary helps assess the quality and completeness of the data and ensures the validity of the analysis. The Case Processing Summary typically includes: Valid Cases: The number of cases included in the analysis, meaning they have complete and usable data for all relevant variables. Excluded Cases: The number of cases removed from the analysis due to missing data, outliers, or violations of assumptions required for discriminant analysis (such as linearity or multicollinearity). Total Cases: The overall number of cases in the dataset, including both valid and excluded cases.

The discriminant analysis is being used to classify companies based on specific performance metrics, the case processing summary will indicate 40 enterprises for before and 40 enterprises for after cluster development approach had complete data and were included in the model, and many were excluded due to missing or invalid data. This summary is essential for understanding the data's quality and ensuring the robustness of the analysis results.

Table 6: Group Statistics

Op		Mean	Std. Deviation	Valid N (listwise) Unweighted	Valid N (listwise) Weighted
0	Ic	2.05	.815	40	40.000
	Sc	2.00	.751	40	40.000
	At	2.13	.723	40	40.000
	Jo	2.03	.698	40	40.000
	Va	2.00	.716	40	40.000
	Ar	2.05	.677	40	40.000
	St	2.23	.768	40	40.000
	Rm	2.03	.660	40	40.000
	Oc	1.98	.660	40	40.000
1	Ic	4.00	.816	40	40.000
	Sc	4.00	.816	40	40.000

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	At	3.98	.832	40	40.000
	Jo	3.95	.876	40	40.000
	Va	3.93	.797	40	40.000
	Ar	3.85	.864	40	40.000
	St	3.83	.903	40	40.000
	Rm	3.85	.893	40	40.000
	Oc	3.88	.883	40	40.000
Total	Ic	3.03	1.273	80	80.000
	Sc	3.00	1.273	80	80.000
	At	3.05	1.211	80	80.000
	Jo	2.99	1.248	80	80.000
	Va	2.96	1.227	80	80.000
	Ar	2.95	1.190	80	80.000
	St	3.03	1.158	80	80.000
	Rm	2.94	1.205	80	80.000
	Oc	2.93	1.230	80	80.000

Source: Computed Data

Group Statistics as per table 6, provides descriptive statistics for the predictor (independent) variables across the different groups (or categories) being analyzed. It helps assess how well the predictor variables distinguish between the groups by showing the variation in the data for each group.

The Group Statistics typically includes: Mean: The average value of the 9 predictor variables within each group (0 and 1), showing the central tendency for that variable within each category. Standard Deviation: A measure of the spread or variability of the predictor variable within each group, indicating how dispersed the values are. Standard Error: The standard deviation of the sample mean, providing an estimate of how much the sample mean is likely to differ from the population mean. Number of Cases: The count of observations or data points available in each group for the predictor variable.

Classify enterprises into "before cluster" and "after cluster" groups, the Group Statistics shows the average profitability (mean) for each group, the variability of profitability (standard deviation), and the reliability of the mean (standard error).

These statistics are crucial for evaluating how effectively the 9 predictor variables separate the 2 groups, with significant differences in the means suggesting that the variables are good at distinguishing between categories.

Table 7: Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
Ic	.406	114.295	1	78	.000
Sc	.375	130.000	1	78	.000
At	.409	112.758	1	78	.000
Jo	.397	118.277	1	78	.000
Va	.377	129.107	1	78	.000
Ar	.420	107.540	1	78	.000
St	.517	72.942	1	78	.000
Rm	.419	108.076	1	78	.000
Oc	.396	118.936	1	78	.000

Source: Computed Data

Tests of Equality of Group Means as per Table 7 is a statistical procedure used to determine if the means of the predictor (independent) variables significantly differ across the groups or categories being analyzed. This test helps assess the ability of the predictor variables to distinguish between the groups based on their means.
The Tests of Equality of Group Means typically involves the following key components: Wilks' Lambda: This statistic tests the overall difference between the groups for each predictor variable. A smaller Wilks' Lambda value indicates stronger discrimination between the groups. It helps assess whether the predictor variable significantly contributes to differentiating the groups. Lower values suggest more distinct group means. F-statistic: This statistic tests the significance of the difference in group means for each predictor variable. A larger F-statistic implies that the predictor

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variable is more likely to differentiate between the groups. Significance Level (p-value): This indicates the statistical significance of the test. A p-value below a specified threshold (usually 0.05) suggests that the means of the predictor variable differ significantly between the groups, indicating the variable's potential for distinguishing between them. Here the values are less than 0.05. The Tests of Equality of Group Means assess whether the differences in predictor variable means across groups are statistically significant. If significant differences are found, it suggests that the predictor variables are effective in classifying the groups in the discriminant analysis.

Table 8: Pooled Within-Groups Matrices[a]

		Ic	Sc	At	Jo	Va	Ar	St	Rm	Oc
Covariance	Ic	.665	.295	-.285	-.501	-.179	.294	.481	.179	-.269
	Sc	.295	.615	.231	-.308	-.487	-.231	.269	.474	.154
	At	-.285	.231	.607	.267	-.296	-.492	-.196	.266	.410
	Jo	-.501	-.308	.267	.627	.254	-.210	-.482	-.235	.241
	Va	-.179	-.487	-.296	.254	.574	.276	-.238	-.429	-.171
	Ar	.294	-.231	-.492	-.210	.276	.603	.314	-.179	-.368
	St	.481	.269	-.196	-.482	-.238	.314	.702	.330	-.162
	Rm	.179	.474	.266	-.235	-.429	-.179	.330	.616	.273
	Oc	-.269	.154	.410	.241	-.171	-.368	-.162	.273	.607
Correlation	Ic	1.000	.461	-.449	-.775	-.290	.464	.704	.279	-.423
	Sc	.461	1.000	.378	-.496	-.820	-.379	.410	.770	.252
	At	-.449	.378	1.000	.433	-.501	-.814	-.300	.434	.676
	Jo	-.775	-.496	.433	1.000	.424	-.341	-.726	-.378	.390
	Va	-.290	-.820	-.501	.424	1.000	.470	-.374	-.721	-.290
	Ar	.464	-.379	-.814	-.341	.470	1.000	.483	-.293	-.608
	St	.704	.410	-.300	-.726	-.374	.483	1.000	.501	-.248
	Rm	.279	.770	.434	-.378	-.721	-.293	.501	1.000	.446
	Oc	-.423	.252	.676	.390	-.290	-.608	-.248	.446	1.000

a. The covariance matrix has 78 degrees of freedom.

Source: Computed Data

The Pooled Within-Groups Matrices as shown in table 8 (also known as the pooled covariance matrix) represent the combined covariance of the predictor variables within each group, assuming that the groups share a common covariance structure. This matrix is crucial for understanding how the predictor variables vary within the groups and is used to calculate the discriminant function, which is central to classifying observations. The Pooled Within-Groups Matrices are derived by pooling the covariance matrices of all groups, assuming that all groups have the same variance-covariance structure. This assumption, known as the homogeneity of variances, is fundamental in linear discriminant analysis (LDA).

Table 9: Covariance Matrices[a]

Op		Ic	Sc	At	Jo	Va	Ar	St	Rm	Oc
0	Ic	.664	.282	-.263	-.488	-.154	.228	.399	.255	-.204
	Sc	.282	.564	.179	-.256	-.385	-.205	.179	.410	.205
	At	-.263	.179	.522	.202	-.282	-.417	-.157	.176	.388
	Jo	-.488	-.256	.202	.487	.179	-.206	-.416	-.231	.180
	Va	-.154	-.385	-.282	.179	.513	.205	-.231	-.333	-.205
	Ar	.228	-.205	-.417	-.206	.205	.459	.194	-.155	-.383
	St	.399	.179	-.157	-.416	-.231	.194	.589	.225	-.174
	Rm	.255	.410	.176	-.231	-.333	-.155	.225	.435	.180
	Oc	-.204	.205	.388	.180	-.205	-.383	-.174	.180	.435
1	Ic	.667	.308	-.308	-.513	-.205	.359	.564	.103	-.333
	Sc	.308	.667	.282	-.359	-.590	-.256	.359	.538	.103
	At	-.308	.282	.692	.332	-.310	-.568	-.235	.355	.433
	Jo	-.513	-.359	.332	.767	.329	-.213	-.547	-.238	.301
	Va	-.205	-.590	-.310	.329	.635	.347	-.244	-.524	-.138
	Ar	.359	-.256	-.568	-.213	.347	.746	.435	-.203	-.353

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	St	.564	.359	-.235	-.547	-.244	.435	.815	.435	-.151
	Rm	.103	.538	.355	-.238	-.524	-.203	.435	.797	.365
	Oc	-.333	.103	.433	.301	-.138	-.353	-.151	.365	.779
Total	Ic	1.620	1.278	.632	.456	.773	1.178	1.265	1.078	.673
	Sc	1.278	1.620	1.165	.671	.494	.684	1.076	1.392	1.114
	At	.632	1.165	1.466	1.165	.609	.357	.556	1.117	1.295
	Jo	.456	.671	1.165	1.557	1.189	.670	.304	.657	1.164
	Va	.773	.494	.609	1.189	1.505	1.150	.545	.466	.757
	Ar	1.178	.684	.357	.670	1.150	1.415	1.039	.655	.503
	St	1.265	1.076	.556	.304	.545	1.039	1.341	1.065	.609
	Rm	1.078	1.392	1.117	.657	.466	.655	1.065	1.452	1.147
	Oc	.673	1.114	1.295	1.164	.757	.503	.609	1.147	1.513
a. The total covariance matrix has 79 degrees of freedom.										

Source: Computed Data

A covariance matrix as shown in table 9 is a square matrix that provides a measure of the relationships (covariances) between pairs of variables in a dataset. It helps to understand how variables vary together, indicating whether they increase or decrease together, and to what extent they are related. In the context of discriminant analysis, covariance matrices are used to assess the variance within each group and the relationships between the predictor variables.

Analysis 1

Box's Test of Equality of Covariance Matrices

Table 10: Log Determinants

Op	Rank	Log Determinant
0	9	-15.917
1	9	-14.891
Pooled within-groups	9	-13.474
The ranks and natural logarithms of determinants printed are those of the group covariance matrices.		

Source: Computed Data

The log determinant as per table 10 is an essential measure in discriminant analysis, particularly when evaluating the variance-covariance structures of the groups. It helps assess the spread of the data within each group, and differences in log determinants can guide model choice (e.g., LDA vs. QDA) and the interpretation of group separation.

Table 11: Test Results

Box's M		150.532
F	Approx.	2.934
	df1	45
	df2	19987.046
	Sig.	.000
Tests null hypothesis of equal population covariance matrices.		

Source: Computed Data

The Test Results as per table 11, in discriminant analysis provide insight into the effectiveness of each discriminant function and the overall model.

Summary of Canonical Discriminant Functions

Table 12: Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	41.350[a]	100.0	100.0	.988
a. First 1 canonical discriminant functions were used in the analysis.				

Source: Computed Data

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Table 12: Wilks' Lambda				
Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.024	275.328	9	.000

Source: Computed Data

Eigenvalues as per table 12, reflect the effectiveness of each discriminant function in separating the groups, with larger values indicating better separation. 0.988 indicates better separation.

Wilks' Lambda as per table 12, tests the overall discriminative power of the model, where smaller values indicate better group separation. Both are crucial for understanding and evaluating the performance of a discriminant analysis model. 0.024 is the smaller value indicate better group separation.

Table 13: Standardized Canonical Discriminant Function Coefficients	
	Function
	1
Ic	.435
Sc	1.071
At	1.138
Jo	.275
Va	1.301
Ar	.765
St	.214
Rm	-.193
Oc	.212

Source: Computed Data

Standardized Canonical Discriminant Function Coefficients as per table 13, provide a way to interpret the relative importance of predictor variables in discriminant analysis, especially when the predictors have different units of measurement. They are calculated by standardizing the predictor variables so that all variables are on the same scale (z-scores). The standardized coefficients show the strength and direction of the relationship between the predictor variables and the discriminant function, helping to identify the key variables that contribute to separating the groups in the dataset.

Table 14: Structure Matrix	
	Function
	1
Sc	.201
Va	.200
Oc	.192
Jo	.191
Ic	.188
At	.187
Rm	.183
Ar	.183
St	.150
Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function.	

Source: Computed Data

The Structure Matrix as per table 14, in discriminant analysis is an essential output that shows the correlations between predictor variables and discriminant functions. These correlations reveal the relative importance of each predictor in separating the groups and help in understanding the classification process. It is an essential tool for interpreting the results of discriminant analysis, aiding in variable selection and providing insight into how each variable influences the group's differentiation.

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Table 15: Canonical Discriminant Function Coefficients

	Function
	1
Ic	.533
Sc	1.365
At	1.461
Jo	.348
Va	1.717
Ar	.986
St	.256
Rm	-.246
Oc	.273
(Constant)	-20.044
Unstandardized coefficients	

Source: Computed Data

Canonical Discriminant Functions: In canonical discriminant analysis, as per table 15, the goal is to find a combination of predictor variables that maximizes the variance between the groups while minimizing the variance within the groups. The canonical discriminant functions represent the linear combinations of predictor variables that can best distinguish between the groups.

A canonical discriminant function for group iii can be expressed as:

$$Di = \sum_{j=1}^{p} \beta ij \cdot Xj + \beta i0$$

Where:

- Di is the discriminant score for group i,
- Xj are the predictor variables,
- βij are the canonical discriminant function coefficients (weights for each predictor variable),
- βi0 is the constant or intercept term.

The discriminant equation is given in [1]

D = -20.044 + .533 Ic + 1.365 Sc + 1.461 At +0.348 Jo + 1.717 Va + 0.986 Ar + 0.256 St -.246 Rm + 0.273 ……………..[1]

Table 16: Functions at Group Centroids

Op	Function
	1
0	-6.349
1	6.349
Unstandardized canonical discriminant functions evaluated at group means	

Source: Computed Data

Functions at Group Centroids are the discriminant function values as per table 16, evaluated at the mean values of the predictor variables for each group. These values help assess the effectiveness of a discriminant analysis model in separating groups and can provide insights into the predictive accuracy and separability of the groups. Understanding these functions allows for better interpretation of the model's performance and decision-making capabilities.

Classification Statistics

Table 17: **Classification Processing Summary**

Processed		80
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		80

Source: Computed Data

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The Classification Processing Summary as per table 17 provides an overall evaluation of the discriminant analysis model's ability to classify observations correctly.

Table 18: Prior Probabilities for Groups

Op	Prior	Cases Used in Analysis	
		Unweighted	Weighted
0	.500	40	40.000
1	.500	40	40.000
Total	1.000	80	80.000

Source: Computed Data

Prior Probabilities for Groups as per table 18 represent the likelihood of an observation belonging to each group before applying any predictor variables.

Table 19: **Classification Function Coefficients**

	Op	
	0	1
Ic	7.022	13.794
Sc	17.436	34.772
At	21.476	40.026
Jo	4.346	8.763
Va	23.916	45.718
Ar	12.593	25.111
St	5.919	9.164
Rm	-4.227	-7.353
Oc	3.574	7.035
(Constant)	-95.202	-349.744
Fisher's linear discriminant functions		

Source: Computed Data

Classification function coefficients as per table 19 are key parameters in discriminant analysis that allow the model to classify observations by weighing the importance of predictor variables and defining decision boundaries between groups. They are critical for understanding the model's behaviour and making accurate predictions.

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Separate-Groups Graphs

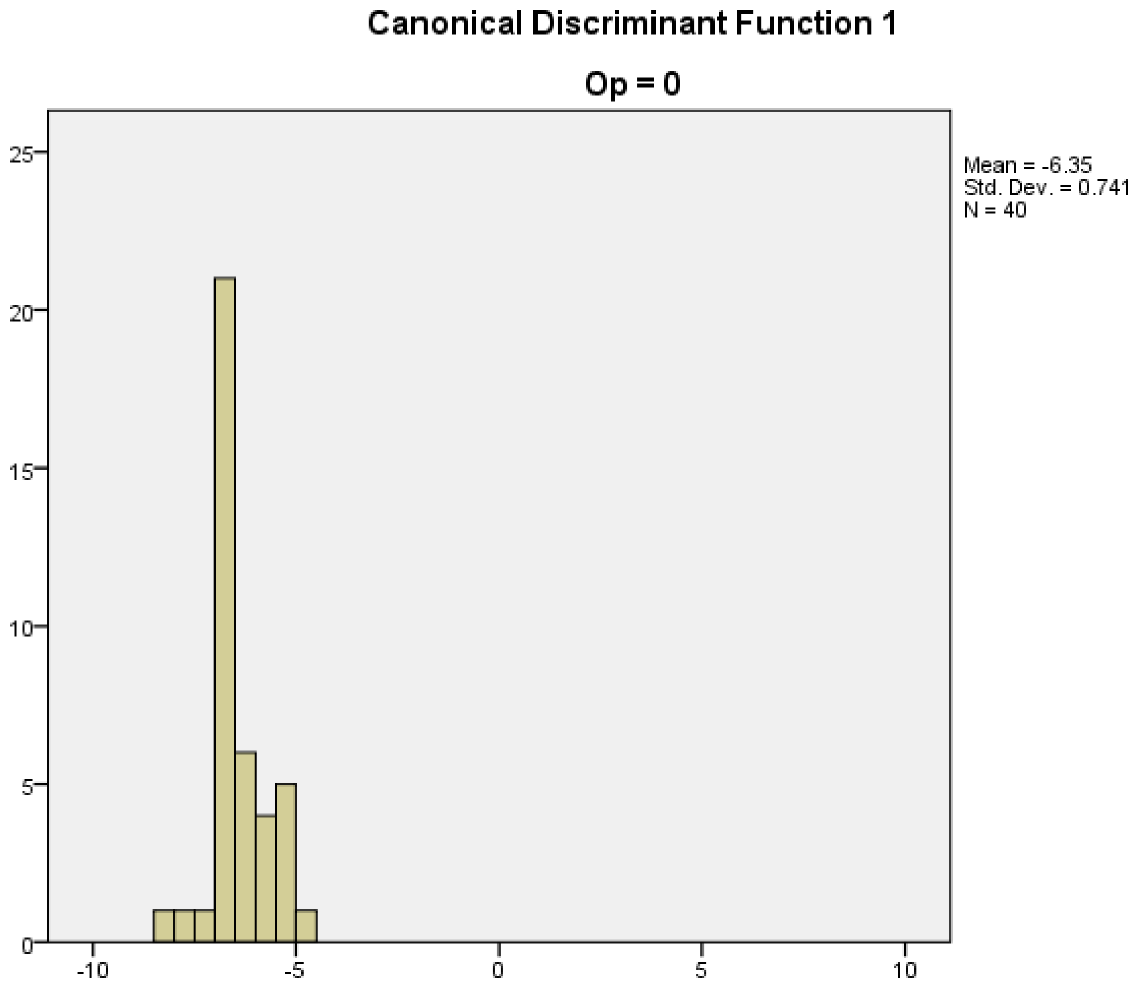

Figure 1: Canonical Discriminant Function. [Op=0]

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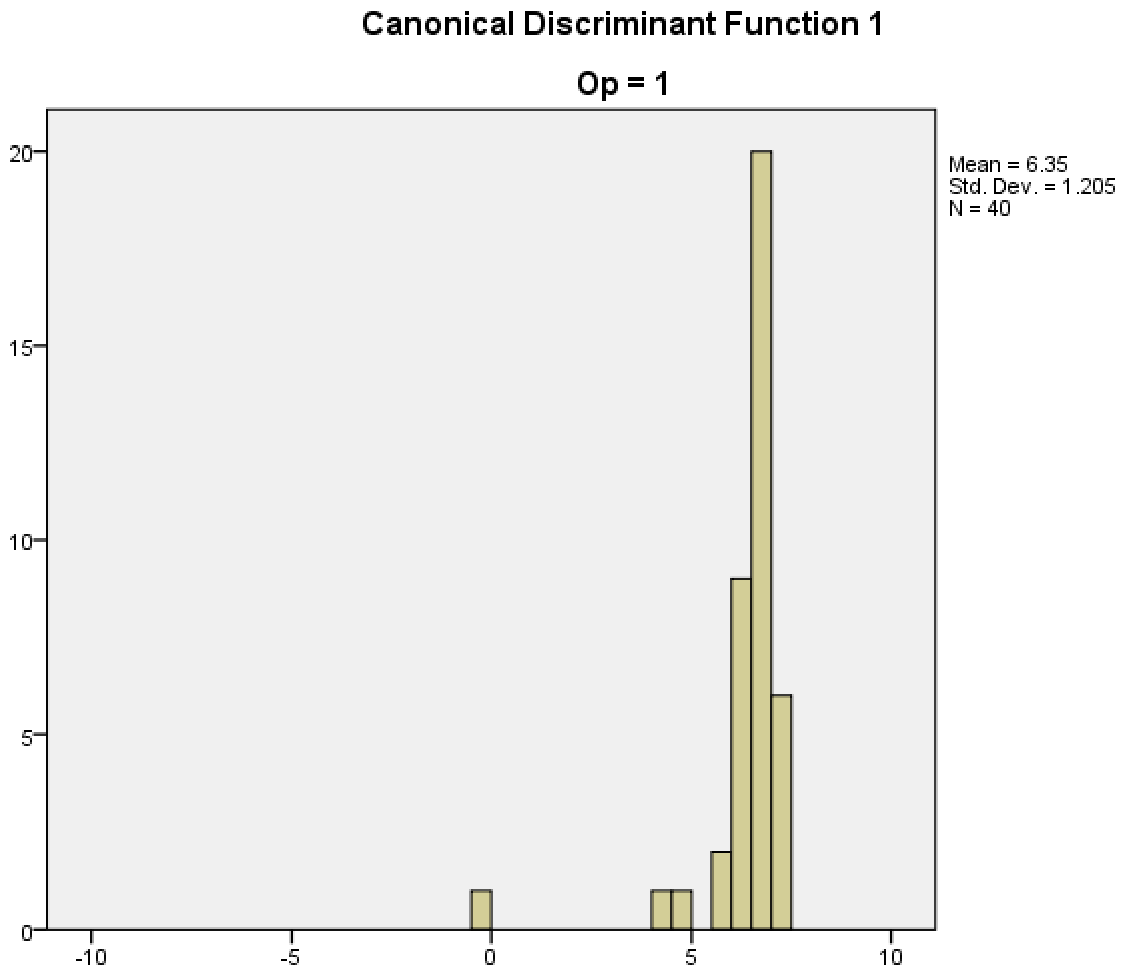

Figure 2: Canonical Discriminant Function. [Op=1]

Table 20: Classification Results[a,c]					
			Predicted Group Membership		
		Op	0	1	Total
Original	Count	0	40	0	40
		1	1	39	40
	%	0	100.0	.0	100.0
		1	2.5	97.5	100.0
Cross-validated[b]	Count	0	40	0	40
		1	1	39	40
	%	0	100.0	.0	100.0
		1	2.5	97.5	100.0
a. 98.8% of original grouped cases correctly classified.					
b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.					
c. 98.8% of cross-validated grouped cases correctly classified.					

Source: Computed Data

Classification Results as per table 20 refer to the outcomes that show how well the model classifies observations (data points) into predefined categories or groups. These results help assess the accuracy of the model in assigning new or unseen observations to the correct group based on the predictor variables.

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The main components of classification results include: Confusion Matrix: A confusion matrix summarizes the performance of the classification model by displaying the count of correct and incorrect classifications. It shows how many observations were correctly assigned to their respective groups and how many were misclassified.

The matrix includes: True Positives (TP): Correctly classified observations for a specific group. False Positives (FP): Observations incorrectly assigned to a group when they belong to another group. False Negatives (FN): Observations that belong to a group but are misclassified as belonging to a different group. True Negatives (TN): Correctly classified observations that do not belong to the target group.

Cross-Validation Results: Cross-validation is a technique used to assess the generalizability of the model. It tests the model on multiple subsets of the data to obtain a more reliable measure of its performance. Cross-validation results help reduce the risk of overfitting and provide a more robust evaluation of the model.

Classification Results in discriminant analysis provide key metrics that assess how well the model classifies observations into predefined categories. These results are essential for evaluating model performance, identifying strengths and weaknesses, and guiding improvements. The evaluation of classification accuracy, error rates, and precision/recall helps ensure that the model is effective and reliable.

Regression Analysis for before and after cluster development approach

Table 21: Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Rmb, Arb, Stb, Icb, Vab, Scb, Atb, Job[b]	.	Enter
a. Dependent Variable: Ocb			
b. All requested variables entered.			

Source: Computed Data

Table 22: Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.897[a]	.805	.755	.327
a. Predictors: (Constant), Rmb, Arb, Stb, Icb, Vab, Scb, Atb, Job				
b. Dependent Variable: Ocb				

Source: Computed Data

Table 23: ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13.666	8	1.708	16.006	.000[b]
	Residual	3.309	31	.107		
	Total	16.975	39			
a. Dependent Variable: Ocb						
b. Predictors: (Constant), Rmb, Arb, Stb, Icb, Vab, Scb, Atb, Job						

Source: Computed Data

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Table 24: Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.861	1.377		1.351	.186
	Icb	-.106	.141	-.131	-.749	.459
	Scb	.088	.166	.100	.532	.598
	Atb	.119	.193	.131	.620	.540
	Job	.181	.207	.191	.875	.388
	Vab	-.055	.156	-.060	-.354	.726
	Arb	-.370	.184	-.380	-2.012	.053
	Stb	-.115	.129	-.134	-.889	.381
	Rmb	.326	.175	.326	1.861	.072

a. Dependent Variable: Ocb

Source: Computed Data

Ocb = 1.861-.106 Icb + .088 Scb + 0.119 Atb + 0.181 Job -.055 Vab -.370 Arb --.115 Stb + .326 Rmb where p= 0.000, $R^2 = 0.805$ ………………………[2]

Table 25: Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.04	2.96	1.97	.592	40
Residual	-.888	.962	.000	.291	40
Std. Predicted Value	-1.582	1.657	.000	1.000	40
Std. Residual	-2.719	2.944	.000	.892	40

a. Dependent Variable: Ocb

Source: Computed Data

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Charts

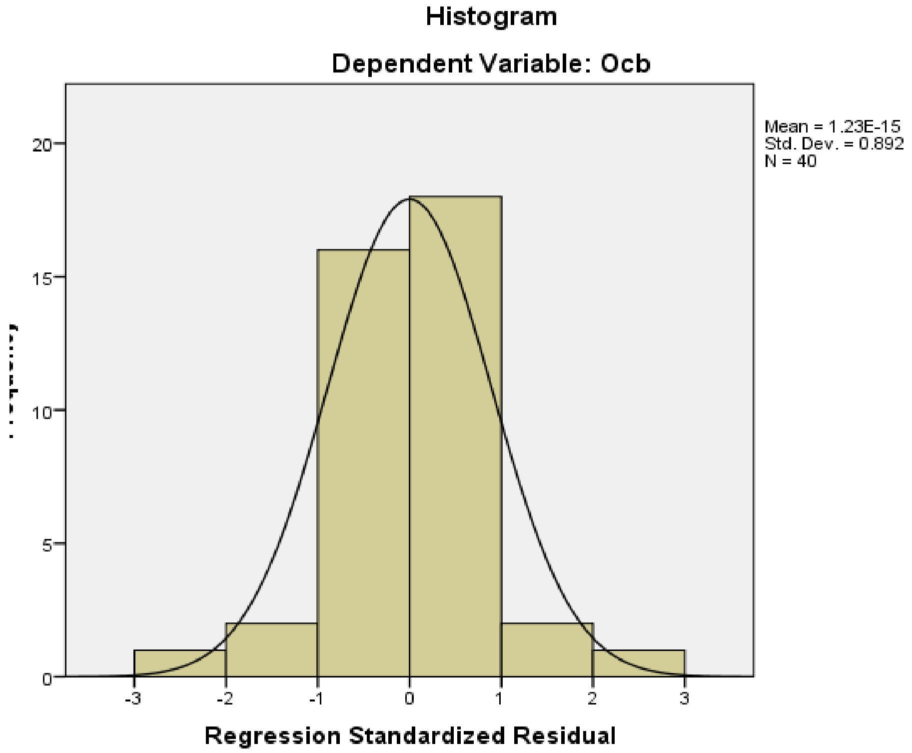

Figure 3: Regression Analysis for before cluster development approach

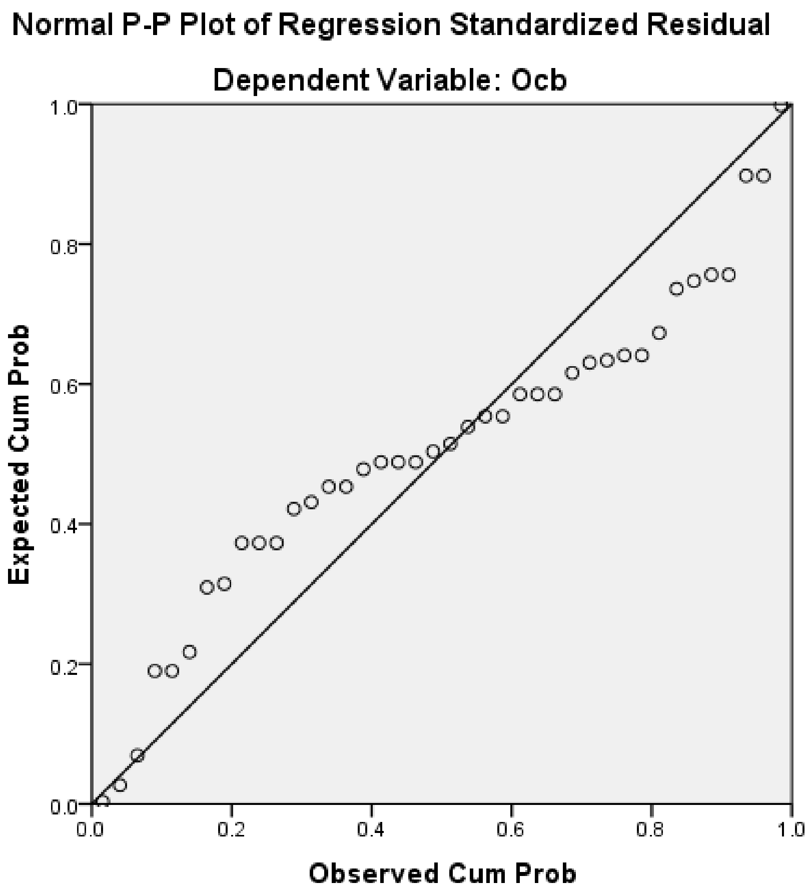

Figure 4: Regression Analysis for before cluster development approach

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Regression

Table 26: Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Rma, Ica, Ara, Joa, Ata, Vaa, Sca, Sta[b]	.	Enter

a. Dependent Variable: Oca

b. All requested variables entered.

Source: Computed Data

Table 27: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.767[a]	.589	.483	.635

a. Predictors: (Constant), Rma, Ica, Ara, Joa, Ata, Vaa, Sca, Sta

Source: Computed Data

Table 28: ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	17.885	8	2.236	5.549	.000[b]
	Residual	12.490	31	.403		
	Total	30.375	39			

a. Dependent Variable: Oca

b. Predictors: (Constant), Rma, Ica, Ara, Joa, Ata, Vaa, Sca, Sta

Source: Computed Data

Table 29: Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.372	2.873		.130	.898
	Ica	.056	.369	.052	.151	.881
	Sca	-.056	.433	-.052	-.130	.898
	Ata	-.196	.378	-.185	-.519	.608
	Joa	.395	.309	.392	1.279	.210
	Vaa	.268	.429	.242	.625	.536
	Ara	-.242	.463	-.237	-.523	.605
	Sta	-.299	.494	-.306	-.605	.549
	Rma	.972	.356	.984	2.728	.010

a. Dependent Variable: Oca

Source: Computed Data

Oca = .372+ .056 Ica --.056 Sca + -.196 Ata + -.395 Joa + .268 Vaa + -.242 Ara --.299 Sta + .972 Rma where p= 0.000, R^2 = 0.589 ………………………[3]

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Charts

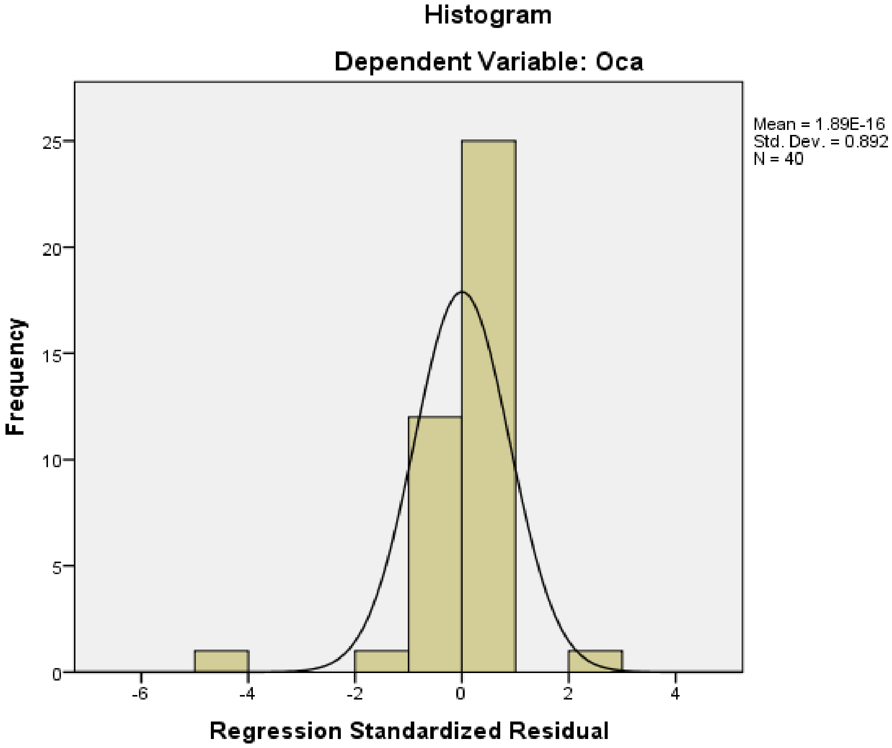

Figure 5: Regression Analysis for after cluster development approach

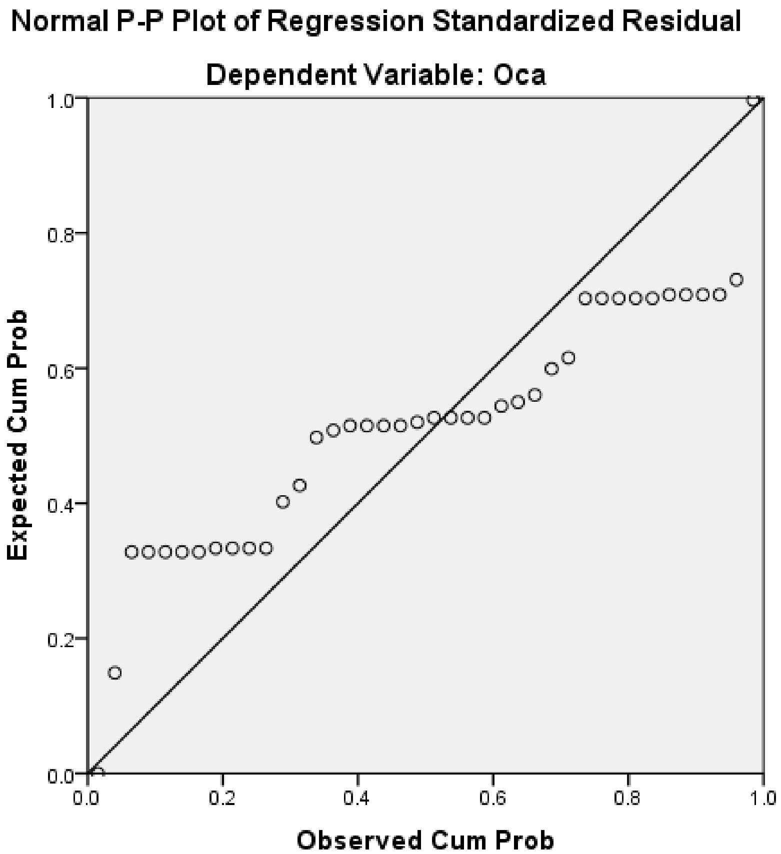

Figure 6: Regression Analysis for after cluster development approach

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Structural Equation Modelling

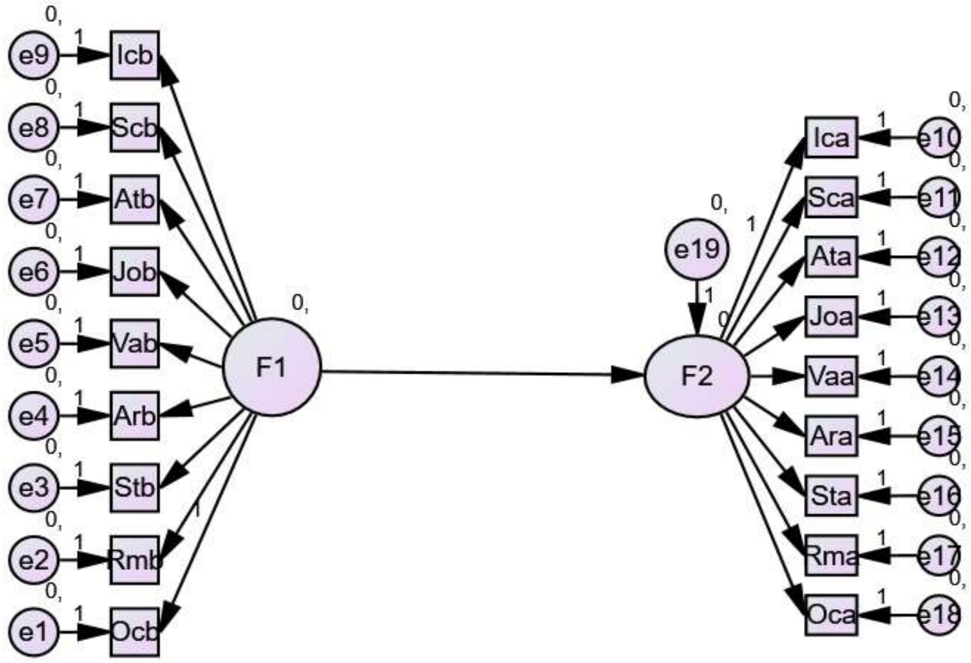

Figure 7: Structural Equation Modelling

Table 29: Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
F2	<---	F1	-.877	.178	-4.924	***	par_17
Ocb	<---	F1	1.000				
Rmb	<---	F1	.389	.171	2.272	.023	par_1
Stb	<---	F1	-.481	.198	-2.432	.015	par_2
Arb	<---	F1	-1.063	.107	-9.931	***	par_3
Vab	<---	F1	-.544	.179	-3.035	.002	par_4
Job	<---	F1	.539	.174	3.099	.002	par_5
Atb	<---	F1	1.102	.119	9.251	***	par_6
Scb	<---	F1	.461	.194	2.374	.018	par_7
Icb	<---	F1	-.635	.203	-3.129	.002	par_8
Ica	<---	F2	1.000				
Sca	<---	F2	.459	.173	2.658	.008	par_9
Ata	<---	F2	-.586	.169	-3.470	***	par_10
Joa	<---	F2	-.960	.146	-6.584	***	par_11

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			Estimate	S.E.	C.R.	P	Label
Vaa	<---	F2	-.309	.175	-1.767	.077	par_12
Ara	<---	F2	.677	.170	3.974	***	par_13
Sta	<---	F2	1.038	.145	7.166	***	par_14
Rma	<---	F2	.278	.198	1.408	.159	par_15
Oca	<---	F2	-.569	.183	-3.115	.002	par_16

Source: Computed Data

Figure 7 and Table 29 reveals that there is significant relationship between input and output variables before and after cluster development approach except Improved market positioning and brand recognition globally.

V. CONCLUSION

The automotive component manufacturing sector in Tirumudivakkam, Chennai, faces several pressing challenges that limit its growth and competitiveness. These challenges include lack of common facility for improvement through targeted investments in technology, workforce training, infrastructure development, and process optimization.

Summary

The Chennai Automotive Common Facility Centre (CFC) is designed to deliver substantial benefits to automotive components manufacturers in Tirumudivakkam, Chennai. By integrating Artificial Intelligence (AI) and robotics, the CFC aims to drive innovation, improve operational efficiency, and enhance the competitiveness of Micro, Small, and Medium Enterprises (MSMEs) in the cluster.

Findings

1. **Innovation and Global Competitiveness**
   - The CFC will empower MSMEs to develop innovative and globally competitive products, improving their market position.
   - AI and robotics will enable precision manufacturing, faster product development, and better customization capabilities.
2. **Comprehensive MSME Support**
   - From concept to commissioning, the CFC will provide comprehensive support, helping MSMEs undertake complex projects and secure high-value contracts.
3. **Access to Advanced Technologies**
   - Cutting-edge technology, such as AI-powered automation, robotics, and advanced testing equipment, will be available, enabling MSMEs to meet global quality and performance standards.
4. **Economic and Employment Growth**
   - Enhanced capacity utilization at both the cluster and unit levels is expected to create more job opportunities.
   - Industries in the cluster could achieve a 10%-15% increase in turnover due to improved efficiency and reduced operational costs.
5. **Value-Added Product Development**
   - The CFC will support the production of higher-value products, allowing MSMEs to capture premium market segments and meet evolving customer demands.
6. **Skill Development and Collaboration**

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- Training programs will enhance the skills of workers, focusing on the application of AI and robotics in manufacturing.
- Common raw material procurement, joint marketing initiatives, and shared infrastructure will foster synergy among cluster members.

7. **Operational Cost Reduction**
    - The shared infrastructure and resources of the CFC will help reduce operational and service costs, boosting profitability for MSMEs.

Suggestions

1. **AI and Robotics Integration**
    - Implement AI-driven predictive analytics to reduce equipment downtime and optimize maintenance.
    - Use robotics for automated assembly lines, material handling, and quality inspection to enhance precision and efficiency.
2. **Collaborative Framework**
    - Develop a digital platform for resource sharing, knowledge exchange, and collaborative innovation within the cluster.
    - Encourage co-development initiatives to maximize the benefits of shared expertise and advanced technologies.
3. **Workforce Upskilling**
    - Organize regular training sessions on advanced technologies like AI, robotics, and smart manufacturing systems.
    - Collaborate with educational institutions and training centers to build a skilled workforce tailored to the industry's needs.
4. **Enhanced Testing and Quality Assurance**
    - Provide AI-powered testing and analytics to help MSMEs meet international certification requirements and expand their market reach.
5. **Focus on Sustainability**
    - Incorporate energy-efficient AI and robotic solutions to reduce environmental impact and align with sustainability goals.

CONCLUSION

The integration of AI and robotics at the Chennai Automotive CFC presents a transformative opportunity for the automotive components manufacturing cluster in Tirumudivakkam. By fostering innovation, reducing costs, and enhancing collaboration, the CFC will significantly improve the competitiveness of MSMEs in global markets. The initiative is also expected to drive economic growth, create employment opportunities, and promote skill development. With strategic planning and stakeholder cooperation, the CFC has the potential to become a model for industrial progress and sustainable development in the region.

Future Direction: The study is conducted in PEC at Chennai and future directions are to study some other clusters in Tamil Nadu and India so as to study the individual cluster model using AI and Robotics integration and finding AI Business Analytics Models like Descriptive Analytics, Diagnostic Analytics, Inferential Analytics, Predictive Analytics, Prescriptive Analytics and Decision Analytics for better cost minimization and profit maximization.

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BIOGRAPHY

Dr. E. Bhaskaran, B.E,M.I.E,M.B.A,PH.D,C.E,F.I.I.P.E,F.I.E, (D.Litt.), (D.Sc.) Life Time Achievement is 1012 Awards and Mementos Received, 131 ISSN Journals Published, 47 ISBN Books Published, 94 Research Papers Presented in National and International Conferences including at Malaysia, Sri Lanka and Thailand, 1333 Invited Talks given including at Singapore and Cambodia, 1453 Training / Workshops /Meetings Attended, 1 Design Registration Patent received from IPR, 1 Product Patent Pending at IPR, 48 Scopus Index Citations, h-index = 5, 712 Google Scholar Citations, 10 ,h-Index, , 13 i 10-index, 14.64 Research Gate Score, 1708 Research Gate Citations, 2,31,216 reads, Empreteco ,152 Violin, Guitar, Piano, and Key Board songs played in Carnatic and western music. They uploaded on You Tube, B.E., with a Best Project Award on Robotics from the Directorate of Technical Education, Government of Tamil Nadu, MBA with Class First Award, Ph.D. with distinction/ highly commended by American University and Calcutta University, Member of Institution of Engineers(MIE), Chartered Engineer(CE), Fellow in Indian Institute of Plant Engineers(FIIPE) and Fellow in Institution of Engineers(FIE)