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Unlocking Effectiveness of MSME Auto Component Enterprises in Chennai Cluster Through Alignment: Evidence of Process - Technology Interaction

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Abstract

Background: A general assumption is technological progress will result in linear improvements in manufacturing performance. This assumption however, does not take into account the contextual realities of Micro, Small, and Medium Enterprises (MSMEs), such as fragmented workflows, limited absorptive capacity, and the coexistence of both legacy and modern technologies under the same roof. These limitations impede the efficacy of technology upgrades in improving output diversity and quality. **Objectives:** This study aims to examine whether the interaction between manufacturing process type and technology class influences output performance in MSME auto component enterprise. It introduces the Dynamic Alignment-Centric Manufacturing (DACM) framework to conceptualise strategic fit as a dynamic, bottom-up capability shaped by contextual intelligence, process-technology coherence, and modular responsiveness. **Methods:** This study utilises primary data collected from 52 MSMEs operating within the Chennai auto components cluster using structured surveys and field observations conducted in 2025. Enterprises were selected using stratified purposive sampling to capture the diversity in process type and technology configurations. Moderation analysis was conducted using linear regression. We utilised path analysis to visually represent the moderation structure and estimate directional relationships. This was followed by slope analysis to interpret the conditional effect across levels of technological sophistication. Flow diagrams, interaction plots, and comparative tables were used to present the results. **Findings:** The study found that neither manufacturing process nor technological sophistication independently predicts output quality or diversity. But their interaction exhibits a significant negative moderation effect, suggesting misalignment can lead to diminished outcomes. The moderation effect was statistically significant, which shows that strategic alignment between process logic and technology class is critical. The slope analysis revealed that advanced technologies may dampen the positive impact of process complexity on output if not properly aligned. These findings confirm the architectural pillars of DACM (contextual intelligence, process-technology coherence, and modular responsiveness) and highlight the need for operator-led adaptation and modular responsiveness in MSMEs. **Significance:** This study extends the strategic alignment theory to MSME shopfloor realities, offering DACM as a grounded alternative to top-down models of smart manufacturing. In contrast to previous studies that focus on technology adoption in isolation, this study integrates process logic, human judgment, and demand variability to explain performance outcomes. It provides actionable insights for policy and practice, recommending that technology interventions be complemented by workflow design, operator training, and scalable integration strategies to enhance absorptive capacity and enterprise agility.

Keywords: MSME; auto component manufacturing; manufacturing workflow; output diversity; moderation analysis; strategic alignment; process-technology alignment

1 Introduction

Studies suggest that technological advancements have consistently enhanced manufacturing operations and functional performance outcomes [(1)],[(2)]. It has been the driving force behind competitiveness in addition to contributing to sustained productivity growth [(3)]. The dynamic market conditions and ambitious performance goals have intensified research in manufacturing technology and industrial engineering to promote sustainable development [(4)]. This has led to the advances in cutting-edge technologies that are reshaping industry structure, organization's internal culture, and production capabilities enhancing operational efficiency and market responsiveness [(5)]. These improvements foster enduring competitive advantage and closely align with firm-level strategic objectives [(6)] consequently capturing the attention of industries across sectors.

In this context, the selection of technology class - defined by its level of sophistication has emerged as one of the critical strategic decisions that influences an organisation's operational structure, functional coherence and production management systems affecting competitive advantage and the pursuit of sustainable growth [(7)]. Periodic technological upgrades are crucial to creating a level playing field for businesses, and pushing early adopters to the forefront of innovation improving their competitive position [(8)].

Manufacturing firms are progressively integrating different technologies to strengthen their technological capabilities in all aspects of their business. This is enhancing execution of process and elevating performance outcomes thereby contributing to overall competitiveness [(3)]. The adoption of information technology tools especially in product and service markets for both customization and channel integration has been shown to drive sustained productivity growth, better market performance, capture more value, and deliver higher stakeholder returns [(9)]. Furthermore, the organisational technology plays a critical role in improving employee productivity thorough strategic alignment within the manufacturing firms [(10)].

Historically, manufacturing relied on legacy machines, static process control methods, and traditional quality control systems that involved periodic checks and batch testing, which often caused inefficiencies due to disruptions, and sub-optimal productivity. Today, most enterprises adopt a comprehensive approach to technology evaluation, prioritising activities that creates higher-value addition and higher-value generation [(11)]. This shift has led to substantial allocation of financial resources towards deploying state-of-the-art machines, automating processes, using industrial robots, and subsequently implementing advanced information systems that gather real-time operational data [(12)]. These systems enable complete visibility of the production process across multiple manufacturing locations through remote monitoring. Additionally, they have demonstrated real-time process optimisation by recognising patterns, faster anomaly detection, and control to reduce variability; ultimately reducing waste, boosting quality, and enhancing efficiency [(13)],[(14)],[(15)]. These also help with root-cause analysis (machine settings, worker skill level, material, and environment) to develop long-term solutions that mitigate recurring issues preventing defects even from remote locations [(16)]. The real-time monitoring and analytics further support informed decision-making including for predictive maintenance to avoid unplanned downtime, and for supply chain optimisation to boost production efficiency and to gain a competitive edge [(17)].

In many organisations, one or more of the technological capabilities appears to dominate the manufacturing process or other pertinent functional areas, thereby shaping performance outcomes [(18)]. Moreover, technology has permeated every aspect of business operations, making it an integral component of all core functional branches significantly enhancing internal and external responsiveness ultimately driving value creation [(19)]. While the paradigm of advanced technologies is still unfolding, it has facilitated inter-firm integration, streamlined workflows across interacting organisations, and contributed to the broader industrial transformation and socio-economic development [(20)],[(21)].

However, despite the evolving technological landscape and the benefits of measurable gains in operational efficiency, product quality, innovation, cost saving, and competitive positioning, scholars have observed MSMEs continue to lag in adopting cutting-edge technologies and only a limited number of MSMEs successfully translating technological integration into superior performance outcomes [22].

Barriers both contextual and institutional such as knowledge gaps that restrict workforce readiness, lack of strategic vision, and fragmented implementation continue to hinder progress [23], [24]. These challenges often result in a convoluted technology adoption landscape, resulting in many businesses falling short of achieving technological maturity, a prerequisite for capitalising opportunities and for promoting sustainability. This suggests that, despite technology's transformative potential, organisational factors deeply influence technology adoption, and its impact on business performance is not always linear [25].

The modern industrial shop floor is much different from the traditional production lines. It is a smart, scalable, networked digital ecosystem, characterised by synergistic linkages between computational elements (AI/ML algorithms, IOT sensor controllers, edge computing nodes, analytics engines, etc.) and physical systems embedded within the digital manufacturing architectures such as, cyber-physical production systems (CPSS), IOT frameworks, MES, SCADA, DCS, HMIs, communication protocols and interoperability layers – the structural, communicative, and operational layers [26], [27]. These systems are designed to enhance capabilities that deliver unprecedented levels of productivity and operational intelligence. The use of Internet of Things (IoT) sensors to provide real-time data input for Artificial Intelligence (AI) and Machine Learning (ML) algorithms is crucial for enabling process optimisation, quality control, and predictive maintenance [28]. Multi-axis robots and autonomous mobile robots (AMRs) operate independently or in conjunction with humans to perform a variety of intricate activities including precision assembly and heavy-load handling [29].

Enabled by Industry 4.0, this shift has given rise to a highly efficient, flexible and data-driven manufacturing environment. At its core, Industry 4.0 and other contemporary digital tools rely on synergistic integration of a number of cutting-edge digital technologies to amalgamate automation, data analytics, and cyber-physical production systems (CPPS) to optimize and transform every aspect of industrial production systems (IPS) to improve agility, responsiveness, and competitive positioning. By combining production data with siloed operational data from ERP, supply chain, and customer support systems, manufacturers' visibility is enhanced, enabling deeper actionable insights to optimise process changes [30]. According to the IBM Institute for Business Value [31], smart manufacturing can boost yields by 20%, detect production defect up to 50%, and increase revenue by almost 8%.

The increased adoption of modern technologies is reshaping the competitive landscape of businesses by streamlining manufacturing to improve operational efficiency [32]. However, the strategic value of contemporary technologies is not exclusively found in their deployment; rather it also depends on how well they are aligned with the dimensions of organizational processes, internal cognitive capabilities, contextual realities, and the broader geo-political, and ecosystem factors; core themes reflected in the alignment literature [33]. All these foregoing challenges get amplified in resource constrained environments such as MSMEs, where limited capacity for strategic planning and integration can exacerbate misalignment – particularly in multi-technology, multi-product settings; where often due to productivity-driven concerns that drives diversification requires frequent calibration of setups and process flow to remain agile and responsive to fluctuating client demands [34], [35].

Therefore, misalignment between technological choice and enterprise manufacturing strategy can adversely impact enterprise performance [36]. Inadequate process orientation and insufficient readiness to handle excessively complex technology, its poor integration, can often result in inefficiencies, resource underutilization, and performance setbacks [37]. This issue is particularly critical in manufacturing settings, where the balance between process design and technological sophistication significantly dictates operational effectiveness, adaptability. and long-term competitiveness [38].

Therefore, the fundamental concern is not about adopting technology, but the strategic alignment of the technological choice with enterprise environment. This underscores the necessity to investigate the intricate relationship between technology class and process design, rather than relying solely on the assumption of a universally linear and beneficial technological effect.

Building on these insights, the following sections articulate the core contributions of this review, identify critical gaps in existing literature, and present the conceptual framework that supports this study. These considerations collectively justify the need for a differentiated perspective on technology adoption within MSMEs. To clarify the scope and direction of this inquiry, the research questions are then introduced, followed by a structured outline of the subsequent sections.

1.1 Research Contributions

This study adds to the body of existing literature on strategic alignment in manufacturing firms by empirically investigating the impact of the relationship between manufacturing process types and technology class on performance in MSMEs. It introduces the DACM (Dynamic Alignment-Centric Manufacturing) framework, which captures the conditional characteristics of process-technology alignment in resource-constrained context.

A key conceptual contribution lies in the integration of Kaplan and Norton's Balanced Scorecard [39] which emphasises strategic alignment across financial goals, customer expectations, internal processes, and learning; and Norman Chorn's

Alignment Theory[40] which focuses on coherence across production, administration, development, and integration. By synthesizing these two perspectives, a multidimensional viewpoint of alignment is presented, that is especially pertinent for MSMEs that manage fragmented workflows and limited resources.

This study applies path analysis and slope analysis on MSME auto component enterprises within the Chennai cluster, to provide a differentiated perspective on the impact of misalignment between process design and technology class on output diversity, quality, and responsiveness especially in build-to-print, multi-product context.

While this study offers a multidimensional view of alignment through the DACM framework, it also responds to several critical gaps in existing literature, particularly in the context of MSMEs and their uneven technological evolution.

1.2 Research Gaps

Previous studies on technology adoption presumes a linear, universally positive correlation between technological sophistication and performance outcomes. But recent research reveals that this assumption overlooks the contextual realities of MSMEs, which encounters limitations in absorptive capacity due to skill deficiencies, fragmented workflows, and lack of coherence[41]. These challenges are further compounded by lack of financial access and inadequate consultative support services (vendor support and implementation expertise), which hinder executing strategic plans and limits the ability to embrace new technologies[22].

MSMEs also exhibit considerable technological inequality relative to big businesses that benefits from advanced integrated systems and better strategic planning capabilities. According to national studies like the MSME Growth Insights Study 2025[42] and CII Digital Readiness Report 2024[43], only 12% of India's 59.3 million registered MSMEs are fully digitally mature. The Digital Maturity Index (DMI) rose only marginally from 56.6 in 2023 to 58.0 in 2025. Small and micro firms averaged scores as low as 1.9 out of 5, while large businesses scored 3.4 out of 5. These geographic disparities further amplify the digital divide. For example, South India has the highest digital adoption rate (DMI 62.9), whereas other regions trail significantly. These findings underscore the digital transformation of MSMEs is very slow. This consequently results in uneven capacity for implementing Industry 4.0 technologies, even within individual units where networked machines and cyber-physical systems require foundational digital infrastructure and strategic coherence.

Despite India's ambition to strengthen its position in the Global Value Chain (GVC), yet many micro and small enterprises continue to rely on legacy machines. Even the adoption of CNC technology, which are generally considered the baseline for smart manufacturing, remains in its early phase of adoption, due to cost barriers, skill gaps, and low absorptive capacity[44]. This shows a gap between aspirational policy and operational realities.

Existing reviews have not sufficiently examined how technology class-defined by its level of sophistication interacts with manufacturing process design in shaping business success. Furthermore, recent developments in smart manufacturing, digital ecosystems, and supply chain integration have not been sufficiently contextualized for MSMEs, particularly in geographically concentrated clusters like Chennai. This study investigates the moderating role of technology class in process-performance relationships, thereby addressing existing gaps.

1.3 Research Questions

RQ1: How does the interaction between manufacturing process type and technology class influence enterprise performance outcomes in MSMEs?

RQ2: Does technology class moderate the relationship between process design and output diversity, quality, and responsiveness?

RQ3: How can strategic the alignment framework be adapted to reflect the conditional nature of technology-process fit in resource-constrained manufacturing environments?

1.4 Conceptual Framework

Grounded in strategic alignment theory and contingency modelling, this study conceptualises enterprise performance as a function of the interaction between manufacturing process design and technology class. It draws on two complementary frameworks: Kaplan and Norton's Balanced Scorecard[39] and Norman Chorn's Alignment Theory[40] which emphasises the need for alignment between internal practices, customer expectations, financial goals, and learning and the need for coherence across production, administration, development, and integration respectively. These perspectives are especially pertinent in the context of MSMEs, characterised by resource constraints and fragmented workflows, underscoring that enterprise success is the outcome of an integrated, context-sensitive approach to performance rather than isolated initiatives.

This study builds on the foundation that elementary expectations and orientation of the manufacturing process are process consistency, technology integration, and responsiveness. These are linked to performance outcomes such as quality, efficiency, and delivery speed. However, the performance outcome can vary widely depending on the superiority of the deployed technology-class (legacy Vs advanced) deployed for the production systems. Technology class thus functions as a contingency variable, conditionally influencing the extent to which process capabilities are converted into performance. Therefore, enterprises deploying technologies with higher levels of sophistication are more likely to achieve higher degrees of quality control, improving both efficiency and market responsiveness, but only if the technologies match the process complexity and absorptive capacity. In contrast, businesses using legacy machines may have limitations in terms of precision, efficiency, and scalability, irrespective of the manufacturing process. In the context of MSMEs, the continued reliance on legacy machines and the slow diffusion of CNC technologies illustrate how practical constraints affect technology-process coherence. These limitations are not to assumed merely technological; they also reflect the deeper fundamental challenges related to absorptive capacity, financial access, and strategic alignment.

As illustrated in Figure 1, the DACM framework formalises this relationship, positioning technology class as a contingency variable that influences the effectiveness of process design through three pillars. It identifies contextual intelligence, process-technology coherence, and modular responsiveness as the architectural pillars for manufacturing agility and production output, each shaped by the overarching influence of demand variability, enabling strategic fit between manufacturing process design and technology class, influencing enterprise performance. These elements illustrate the dynamic, bottom-up characteristics of MSME operations, wherein strategic alignment arises from adaptive execution rather than rigid planning. Path analysis and the slope analysis provide empirical validation that confirms misalignment between process and technology class can lead to performance setbacks, whereas strategic fit enables competitive advantage. Figure 1, presents the DACM framework.

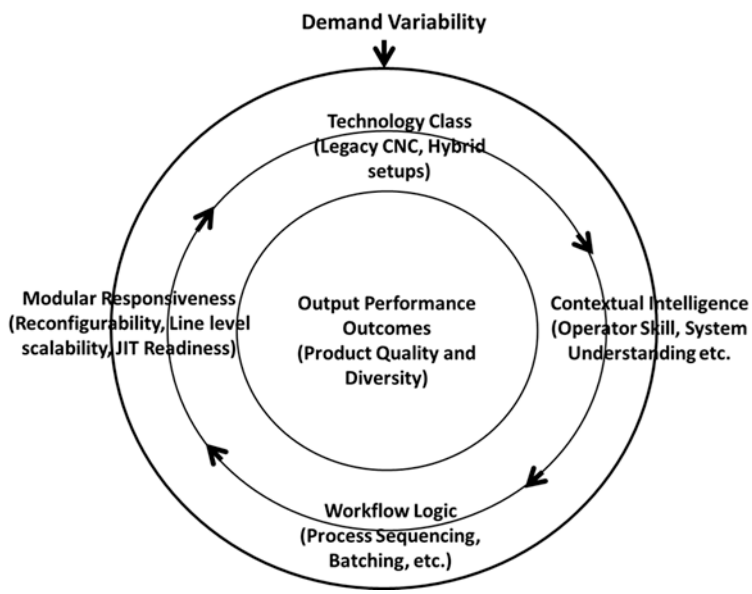

Fig 1. DACM Framework: Strategic Fit Through Technology-Process Alignment

As illustrated in Figure 1, the DACM framework shows how internal capabilities such as contextual intelligence, process-technology coherence, and modular responsiveness interact with external variability, particularly demand fluctuations, to shape MSME operations affecting manufacturing agility and output performance. These elements operate cohesively in a dynamic way, enabling businesses to convert process capabilities into product quality and diversity. This model reinforces that strategic alignment is not a static design choice, but an emergent outcome of adaptive execution in resource-constrained environment.

2 Research Methodology

2.1 Research Design

This study applies a quantitative, exploratory and explanatory research approach to determine if the deployed technology class moderates the relationship between the manufacturing process used by MSMEs and the diversity of auto components they manufacture. A contingency-based framework forms the basis of the research design, in which technology configuration interacts process design to influence production orientation.

2.2 Data Collection and Sampling

2.2.1. Target Population

MSME ancillary units operating in the Chennai auto component cluster, engaged in build-to-print, and multi-product manufacturing.

2.2.2. Sampling Frame

Stratified Purposive sampling was applied to capture the diversity in manufacturing process types, technology classification, and auto component group orientation.

2.2.3. Data Source and Sample Size

Structured survey and field observations were conducted in 2025. The data was gathered from 52 businesses. The survey targeted entrepreneurs, shop-floor managers, and production supervisors.

2.2.4. Data Collection Instrument

Structured questionnaire covering process design, technology class, and auto component group orientation.

2.2.5. Unit of Analysis

Individual enterprise-level data that includes manufacturing process type, technology class, and auto component group orientation.

2.3 Variable Definitions (Table 1)

Table 1. Variable Definition and Measurement

Construct	Definition	Measurement
Manufacturing Process Type (MP)	As defined by the production workflow logic: Repetitive, Discrete, Mixed (Repetitive & Discrete), and Batching.	Categorical Variable with four levels (multilevel)
Technology Class (TC)	Based on machine capability: Formative, Substrative, and Batching. This captures functional specialization.	Categorical Variable with three levels (multilevel)
Auto Component Group Orientation (APP)	Derived from survey responses indicating product groups the firm produces in other words the firm's product group orientation:Engine & Engine components, Drive & Transmission, Suspension, Wheel & Braking, Electrical & Electronic Systems, Rubber components, Automotive Plastics, Interiors & Upholstery, Paints & Other Chemicals, and Others	Categorical Variable with 10 levels (multilevel)

1. Most MSMEs use a mix of Technology Class and to meet variable demand, workflow process logics are frequently reconfigured to service multiple product groups enabling product versatility, underscoring strategic adaptability to build capability portfolio rather than rigid specialization.
2. Interaction Term (InterMPTC) created to test moderation effect. Centered by centering and multiplying MP * TC.
3. Outcome Variable (APP) Highlights the diversity of auto component product groups, serving as a proxy for production orientation, reflecting the enterprises' ability to diversify output in response to product variability and operational flexibility.

This study assessed three latent variables: Manufacturing Process (MP), Technology Class (TC), and Auto Parts Produced (APP). The moderating role of MP and TC was tested using an interaction term (InterMPTC), constructed by centering MP and TC before multiplication. The variables were transformed by subtracting their respective sample means, resulting in CenterMP, and CenterTC. This approach mitigates multicollinearity and ensures interpretability.

2.4 Analytical Strategy

The three primary variables, Technology Class (TC), Manufacturing Process (MP), and Auto Component Group Orientation (APP) were considered as categorical variables with multiple levels based on field observations and firm-reported classifications. These observed variables were dummy-coded to represent the collective categories i.e. their respective full set, and then mean-centered for regression and SEM-Path Analysis. The study used computed categorical variables for moderation analysis, which is in line with the conceptual framework and the data structure. To mitigate multicollinearity and to improve interpretability the MP and TC variables were mean-centered before constructing the interaction term (InterMPTC) using SPSS Compute Variable function.

1. Path Analysis: To examine the direct and indirect relationships between the construct
2. Moderation Analysis: Multiple linear regression was conducted using with interaction term (MP * TC) to test the conditional effect on APP.
3. The analytical model was estimated using path analysis to examine the directional relationship. AMOS v.30 was used to derive the regression weights and to interpret the strength and significance of each path.
4. Slope Analysis is used to interpret how different technology classes relate to process types affecting the auto component diversity.

2.5 Moderation Structure

Figure 2 illustrates how technology class (TC) moderates the relationship between manufacturing process (MP) and application performance (APP). This highlights the conditional nature of process-technology alignment in MSMEs.

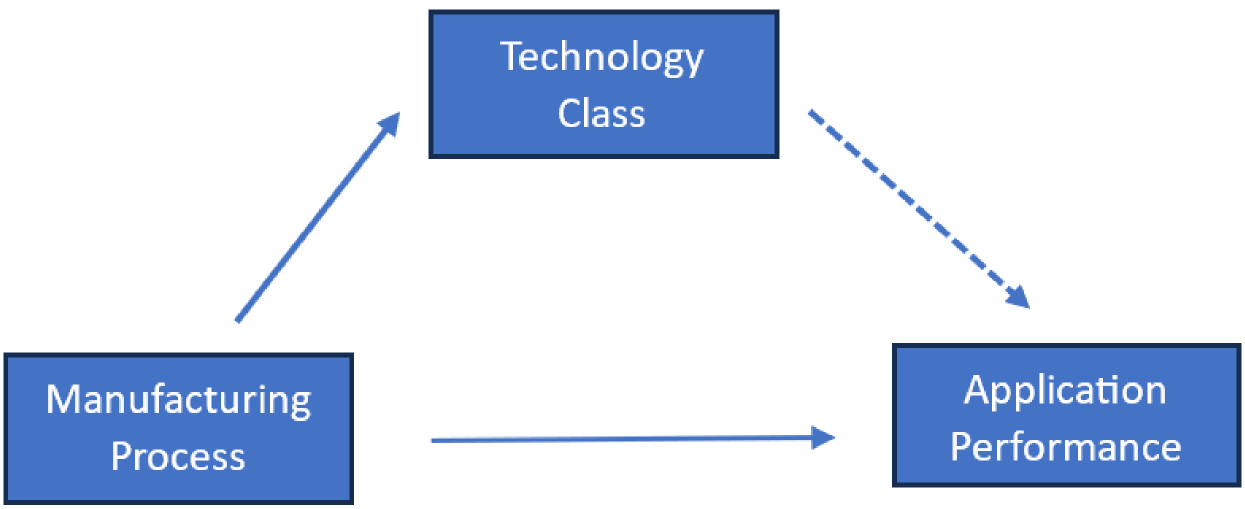

Fig 2. Interaction Between Manufacturing Process and Technology Class Influencing Application Performance

While the figure may visually suggest a mediating pathway, the present study tested Technology Class (TC) as a moderator using interaction term (InterMPTC). We acknowledge that TC could also be conceptualised as a mediator, which is a broader theoretical possibility and may be an avenue for future research.

2.6 Limitation of the Study

A key limitation of the study is the modest or relatively small sample size (n = 52), which may increase risk of model fit issues, large standard errors, potential Type 2 errors, normality issues, and reduced generalisability. However, in this study tested only three parameters (latent variables), and following the conventional rule of thumb of 5-10 observations per estimated parameter[45], [46], the sample size remains within the acceptable range for exploratory analysis with 10-15 cases per predictor guidelines. We therefore interpret the results with caution and emphasise that this study serves as a exploratory/pilot investigation. Further research with larger samples will be necessary to validate and extend the DACM framework.

3 Data Analysis and Interpretation

3.1 Overview of the Analytical Approach

This section presents the statistical results. A moderation analysis was performed to determine whether the relationship between the manufacturing process type and auto component diversity is conditioned by the technology class. The analysis was carried out using linear regression modelling, with centered variables and interaction term that represented the cumulative effect of process and technology configuration.

Information was collected from 52 MSMEs in the auto component sector. These businesses use a mix of subtractive, formative and batching oriented machine technologies along with multiple process types to allow for flexible production methods.

The variables were coded and centered to examine main and interaction effect. Specifically, the Manufacturing Process (MP) and Technology Class (TC) were transformed by using the Compute Variable function in SPSS. Subsequently, the interaction term (InterMPTC) was computed as the product of CenterMP and CenterTC. The centering and interaction term construction steps were performed using SPSS to ensure consistency and reproducibility of the analysis. This procedure reduces multicollinearity and improves interpretability of the regression coefficients.

APP = Auto Parts Produced (outcome variable)

CenterMP = Centered Manufacturing Process (Main Effect)

CenterTC = Centered Technology Class (Main Effect)

InterMPTC = Interaction Term of MP*TC

To strengthen the validity of our findings, we adopted methodological triangulation. In addition to regression analysis, SEM path analysis was used to visualize and estimate the directional effects, and slope analysis was applied to interpret the moderation across the levels of Technology Class. This triangulation ensured that the inferences were not solely dependent on any one method, but were supported by converging evidences across methods.

3.1.1. Results and Findings

3.1.1.1. Moderation Analysis. The study assessed the moderating role of Technology Class (TC) on the relationship between Manufacturing Process and Auto Parts Produced (APP).

H1a: The interaction between manufacturing process type and technology class has a significant and meaningful impact on diversity of auto parts produced.

3.1.1.2. Path Analysis. The path diagram in Figure 3 illustrates the moderation framework used for the analysis, with Auto Parts Produced as the outcome variable, shows the moderating relationship between the manufacturing process type (Center MP), technology class (Center TC), and the interaction term (InterMP). Centered variables are employed for main effects, while the conditional influence of technology on the process-output connection was represented by a computed interaction term (Inter MPTC).

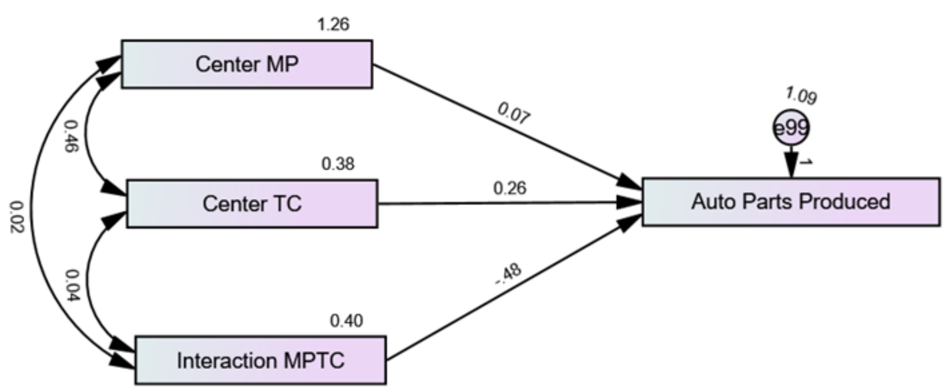

Fig 3. Moderation Path Model: Process Type * Technology Class ⊠ Auto Parts Produced

The path coefficients are based on the unstandardised estimates reflecting the directional impact of each predictor on the outcome variable.

The regression output for the moderation model investigating the combined impact of technology class (Center TC), manufacturing process type (Center MP) and their interaction (Inter MPTC) on the diversity and quality of auto parts produced (APP) is shown in Table 2.

Table 2. Moderation Analysis Summary

Predictor	Estimate	S.E.	C.R.	P	Interpretation
APP CenterMP	.073	.175	.420	.674	Not Significant
APP CenterTC	.259	.319	.810	.418	Not Significant
APP InterMPTC	-.476	.234	-2.033	.042	Significant

The results revealed, both main effects (Manufacturing Process and Technology Class) are statistically insignificant, suggesting they lack a strong linear impact on the output of the auto parts produced. However, the interaction between MP and TC exhibited a negative and statistically significant moderating impact on APP with (b = -.476, t = -2.033 and p = 0.042), thus supporting H1. The results also suggest that the effect is interaction-driven as opposed to isolated enhancements, reinforcing the joint dynamics between MP and TC are predominant in influencing production output and quality. While Table 2 presents the regression coefficients for the model, Table 3 interprets these results to illustrate the conditional effect of Technology Class.

Table 3. Interpretation of Results

Path	Estimate	Interpretation
APP CenterMP	0.07	On an average, APP rises by 0.07 units for every unit change in manufacturing process type, however, as p = 0.674, this is not statistically significant. The main effects are weak and statistically insignificant. Therefore, variations in output and quality cannot be meaningfully explained solely by process type.
APP CenterTC	0.26	On average, APP rises by 0.26 units for every unit increase in technology class sophistication, however, as p = 0.418, this is not statistically significant. The main effects are weak and statistically insignificant. Therefore, variations in output and quality cannot be meaningfully explained solely by technological sophistication.
APP InterMPTC	-0.476	The suggests, on average, the interaction between MP and TC lowers APP by 0.48 units. The negative sign and the significant p value (.042) confirms that when process and technology are misaligned, manufacturing efficiency drops.

The analysis suggests that neither the manufacturing process nor the technology class independently impacts nor can predict the output of the parts produced in a significant manner, however their interplay is significant and negative. This suggests a moderating effect, where the impact of one variable say MP on the output of APP relies on the level of Technology Class. This implies that adoption of latest technologies would not necessarily guarantee increased production output unless they are aligned with suitable production processes. Alternately, if process improvements are not accompanied with appropriate technologies, they might not produce the desired effects. This finding underscores the importance of strategically integrating process design with technology choices to maximise production efficiency in MSME auto component enterprises. These findings lead us to conclude that process misalignments, in particular when they are not strategically aligned with technological sophistication, can undermine enterprise performance. The findings also imply, MSMEs may be able to achieve higher performance gains of 40-50% or more including significant reduction in production defects by actively aligning MP logic with TC. This exceeds IBMs benchmark of a 20% yield increase for smart manufacturing that assumes alignment between people, process and technology.

3.1.1.3. Slope Analysis.

H2a: Technology Class negatively moderates the relationship between manufacturing process and diversity of parts produced, such that a higher technological sophistication of TC weakens the positive impact of MP configuration and output diversity.

To better understand the nature of the moderating effect, a simple slope analysis conducted, to assess the role of TC on the relationship between MP and APP. The slope is illustrated in Figure 4. As can be observed from the interaction plot, the line is much steeper for low levels of TC and the regression lines intersect, suggesting differential effect of manufacturing process on the diversity of output of the auto parts produced across levels of TC. At lower levels of Technology class, the impact of increase in manufacturing process complexities on the output of the APP is much stronger. However, at cutting-edge levels of TC, despite an increase in intensity of MP, the strength of the relationship with APP decreases. This indicates a negative moderation effect. According to this finding, process complexity on production output may be moderated and potentially dampened by advanced technologies. In conclusion sophisticated TC weakens the impact of MP on APP.

Note: Interaction plot generated using an Excel-based Statistical Package developed by James Gaskin.

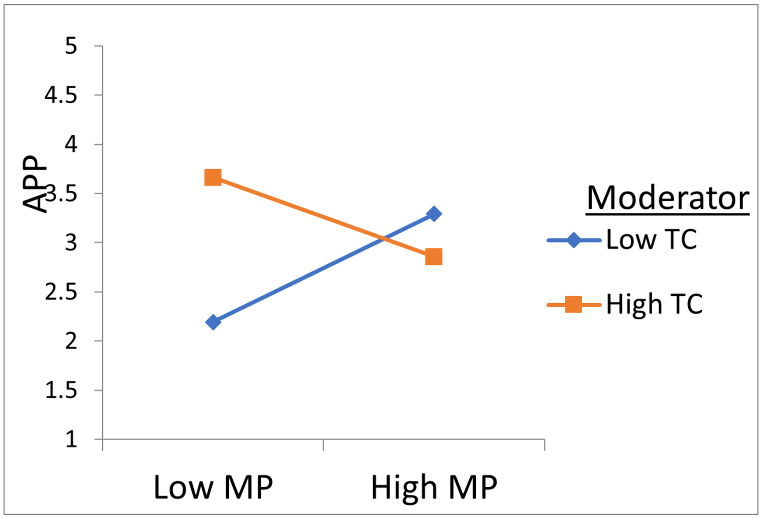

Fig 4. Slope Analysis showing interaction between MP and TC on APP

In a multi-machine and multi-process setting like MSMEs, the findings suggests that the incorporating advanced technologies without aligning them with suitable process workflows may unintentionally affect the quality and diversity of components produced. Businesses may still encounter operational bottlenecks and decreased productivity if their workflow logics are misaligned with the machines intended functional application despite advanced technology portfolios.

3.1.1.4. Hypothesis Summary. Hypothesis H1a is supported, confirming strategic alignment between manufacturing process and technological class is essential for unlocking manufacturing effectiveness. Even though individual main effects were statistically insignificant, their interaction was observed to be statistically significant and negative, confirming the moderating role of technology class.

Furthermore, Hypothesis H2a is also supported, indicating when advanced technologies when misaligned with process configurations, can negatively impact output, affecting both output diversity and quality.

These findings are crucial in MSME settings characterised by their on-the-fly adaptiveness and responsiveness in meeting variable demand in the auto component sector. The findings challenge the conventional supposition that output growth and quality enhancements can be achieved through technology upgrades alone. The findings imply it is crucial to align workflow process logic with the technology class installed for improving output efficiency and highlight the need for integrated alignment to sustain competitiveness in MSME environment.

3.1.1.5. Rationale of the Study. These results reinforce the DACM frameworks focus on contextual intelligence, process-technology coherence and modular responsiveness as critical enablers of manufacturing agility. This methodical approach recognises MSMEs, as highly adaptive businesses, that frequently reconfigure their manufacturing process and technological setup to improve operating equipment efficiency (OEE), minimize machine idle time, and respond to variable market demand. Such adaptations enable to expand enterprise capability portfolio and product basket diversification within the just-in-time value chains. The negative moderation effect observed in the statistical analysis supports the hypothesis that process workflows and technological capabilities can both shape and limit the quality and diversity of output. This underscores the critical role of strategic alignment in shaping manufacturing effectiveness and enterprise competitiveness. These results reinforce the DACM frameworks focus on contextual intelligence, process-technology coherence and modular responsiveness as a critical factor that enable manufacturing agility.

3.1.2. Discussion: Interpreting DACM in MSME Context

The findings from the moderation and slope analysis strongly supports the DACM framework. MSMEs particularly those in the auto component sector, operate under conditions of high variability in demand variability, constrained resources, and fragmented workflows. These businesses typically operate with a mix of legacy hardware and modern technologies[41], frequently reconfiguring their manufacturing processes to respond to shifting customer requirements and short-run production demands [47]. This adaptive behaviour aligns with the DACM's architectural pillars: contextual intelligence, process-technology coherence, and modular responsiveness.

The statistically significant negative moderation effect observed in the interaction between manufacturing process type and technology class highlights a critical insight: misalignment between process complexity and technological sophistication can dampen performance outcomes, especially when it comes to quality and product diversity. This finding contradicts the popular belief that productivity rises automatically with the adoption of advanced technologies. Even modern technologies can fail to deliver in an agile MSME environment, where legacy and modern systems work together, and short-run, multi-product manufacturing is the norm.

These empirical observations contribute to the literature on manufacturing systems by establishing adaptability in MSMEs as a dynamic balance between machine capabilities, workflow logic, and planned sequencing rather than a result of isolated technology upgrade. The study expands the alignment theory, as articulated by Kaplan & Norton and Norman Chorn, to the MSME shopfloor, where alignment is influenced not by enterprise strategy alone, but by the interaction of workflow logic, technological capability, and demand variability.

DACM frames enterprise effectiveness as a dynamic function of fit-for-purpose workflows, machine capabilities, modular responsiveness, and contextual intelligence. While process-machine dimension has been discussed earlier, modular responsiveness and contextual intelligence emerge as critical enablers in volatile demand environments. These are characterised by:

- Reconfigurable Workflows: Ability to adjust process sequence depending on the product or order size.
- Scalable Integration: Ability to add new machines or undertake modifications to them, and operations can be taken up without disrupting the entire operations.
- Line-level Adaptation: Ability to reconfigure specific sections without an enterprise level intervention.
- Support for Multi-product Manufacturing: Allows quick reconfiguration of process for transition between products and product groups to support JIT paradigm.
- Operator led-adaptation: using human judgement to make sure decision made on the shopfloor are aligned with technical limitations and customer expectations.

These aspects show that DACM is a bottom-up orientation, contrasting with static, top-down models. The framework shifts analytical focus to the shopfloor, where machine capabilities, human judgement, and process logic interact dynamically to shape performance. This approach enhances machine-level efficiency, enterprise responsiveness, and eases the ability to evaluate fit-for-purpose configurations.

At the production level, DACM identifies contextual intelligence, process-technology coherence, and modular responsiveness as the architectural pillars for manufacturing agility and output performance. All components are influenced by demand variability, which acts as the outer shell in the model's graphical representation. The innermost shell represents product quality and diversity suggesting the micro-output realities shaped by layered influences. The visual representation supports DACMs core proposition: operational alignment is a dynamic system-level capability, not a static design choice.

From a policy and practice perspective, this study suggests that technological intervention should extend beyond subsidizing equipment purchases. They must include operator-level training, workflow redesign support, and modular integration strategies. These elements collectively enhance process-technology alignment, improve responsiveness, and raise production efficiency; making MSMEs not just digitally equipped, but strategically agile.

4 Conclusion

This study examined the conditional relationship between manufacturing process design and technology class in shaping output performance among MSME auto component enterprises. Through moderation and slope analysis, it was found that neither process complexity nor technological sophistication independently predicts production diversity or quality. Instead, their interaction and the degree of strategic alignment between them, emerges as critical determinant of manufacturing effectiveness.

The findings challenge the widespread assumption that productivity gains are a direct consequence of technology upgrades. In MSMEs, it is typical to find legacy and advanced systems to work together. The production is characterised by short-run, multi-product workflows. In such kind of settings, a mismatch between process logic and machine capability can impede performance. This highlights the necessity for a more nuanced understanding of manufacturing agility; one that considers contextual realities, operator judgement, and modular adaptability.

To address this gap, the study proposes the Dynamic Alignment-Centric Manufacturing (DACM) framework. DACM conceptualises enterprise performance as a dynamic function of contextual intelligence, process-technology coherence, and modular responsiveness, all shaped by demand variability. It shifts the analytical focus from static strategy models to the real-world operations of business, offering a realistic view for understanding to plan how to enhance MSMEs agility.

From a policy and practice standpoint, the study recommends that technology interventions can be complemented by operator training, workflow redesign support, and modular integration strategies. These factors collectively strengthen absorptive capacity, refine process-technology alignment, and elevate enterprise responsiveness. Thereby empowering MSMEs to transcend beyond mere technology purchase and achieve higher degrees of operationally flexibility alongside strategic agility.

While the study is exploratory in nature and based on a modest sample size, the use of methodological triangulation and careful coding procedures strengthens confidence in the findings providing a foundation for future research. Future research could broaden DACM application to other manufacturing clusters, investigate its applicability in service-oriented MSMEs, and examine its role in supply chain integration. DACM offers scalable framework for improving productivity, resilience, and competitiveness in resource-constrained industrial settings by bridging theory and practice.

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