A Multi-Dimensional Framework Using Maturity Modelling and Structural Equation Analysis for Assessing Industry 4.0 Readiness in Indian Automotive Manufacturing

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***Abstract*—India's automotive industry is one of the largest in the world, contributing 7.1% to national GDP and employing over 35 million people directly and indirectly. Despite growing interest in Industry 4.0 (I4.0), a significant gap persists between the digital transformation aspirations of Indian automotive firms and their actual readiness to achieve it. This paper presents the Industry 4.0 Maturity Assessment Model for Indian Automotive Sector (I4MAM-IAS) — a novel, contextualised seven-dimension framework validated through a comprehensive empirical study of 55 Indian automotive firms (30 OEMs and 25 Tier-1 suppliers), yielding 387 valid survey responses from the Delhi NCR region. The study integrates a 35-item structured instrument, Structural Equation Modelling (SEM), K-means cluster analysis, one-way ANOVA, and a Performance Evaluation Index (PEI) comprising 47 validated Key Performance Indicators (KPIs) across five critical domains. Key findings reveal that: (i) technological infrastructure ($\beta = 0.57$, $p < 0.01$) and organisational culture ($\beta = 0.32$, $p < 0.05$) are the strongest predictors of maturity; (ii) 73% of firms are concentrated at Levels 2–3 (Beginner to lower Intermediate); (iii) a critical self-assessment bias exists, with 97.67% of firms self-reporting as Level 5 while objective assessment places virtually all below Level 3; and (iv) training budget alone ($\beta = 0.11$, $p = 0.18$) is not a significant predictor of workforce readiness. The paper offers actionable recommendations for manufacturing managers, policymakers, and researchers working toward smart manufacturing in emerging economies.**

***Index Terms*—Industry 4.0; maturity model, Indian automotive manufacturing, SEM, digital transformation, emerging economies, PEI, readiness assessment**

I. Introduction

The Fourth Industrial Revolution — broadly known as Industry 4.0 — is reshaping global manufacturing through the convergence of Cyber-Physical Systems (CPS), Internet of Things (IoT), Artificial Intelligence (AI), Big Data Analytics, cloud computing, and advanced robotics. Unlike its predecessors, this revolution demands not merely technological investment but a systemic transformation across strategy, organisational culture, workforce capabilities, and inter-firm collaboration (Lasi et al., 2014). The automotive sector has historically been among the earliest adopters of manufacturing innovation, and today's global leaders integrate robotics, AI-driven quality control, digital twins, and IoT-enabled logistics into their core production processes (Frank et al., 2019).

India's automotive sector sits at a critical crossroads. The country is the world's fourth-largest automobile producer, manufacturing over 28 million vehicles in 2023–24 alone, contributing approximately 49% to

India's manufacturing GDP and forming a central pillar of Make in India and Atmanirbhar Bharat policy ambitions. Yet, large-scale Industry 4.0 adoption in Indian automotive manufacturing remains uneven, fragmented, and inadequately measured. While OEMs such as Maruti Suzuki, Tata Motors, and Bajaj Auto have made visible investments in automation and digital systems, the vast majority of Tier-1 suppliers continue to operate with legacy equipment, manual workflows, and limited digital infrastructure (Noor & Kumar, 2023).

A fundamental challenge is the absence of an India-specific, empirically validated maturity assessment framework. Global models such as the Acatech Maturity Index (Schuh et al., 2017) and the IMPULS Readiness Model were designed for advanced industrial economies and assume infrastructure standards, workforce literacy, and investment capacity that do not reflect Indian realities. Applying these frameworks without contextual adaptation leads to distorted self-assessments and poor resource allocation (Mittal et al., 2018).

This paper addresses this gap with three contributions: (1) Development of the I4MAM-IAS model — a seven-dimension, 35-item maturity assessment instrument adapted to the Indian automotive context; (2) Empirical validation across 55 firms using PLS-SEM, cluster analysis, ANOVA, and CFA; and (3) Development of a 47-KPI Performance Evaluation Index (PEI) quantifying operational, quality, cost, innovation, and sustainability outcomes.

II. Literature Review

2.1 The Concept of Industry 4.0 and Its Core Technologies

The term 'Industry 4.0' was formally introduced in Germany in 2011 and describes the fourth industrial revolution characterised by integration of digital and physical manufacturing systems (Lasi et al., 2014). Its core technological pillars — IoT, CPS, AI, Big Data, cloud computing, robotics, digital twins, and additive manufacturing — enable smart factories where machines communicate, self-optimise, and make autonomous decisions (Öztemel & Gursev, 2020). Unlike earlier revolutions driven by single technologies, Industry 4.0 demands simultaneous transformation across technology, people, processes, and strategy (Ghobakhloo, 2020).

Digital twin technology has emerged as one of the most impactful enablers of smart manufacturing. Tao et al. (2018) demonstrated that digital twin-driven product design, manufacturing, and service systems — powered by big data — significantly improve efficiency, sustainability, and product lifecycle management. Despite high reported impact, digital twin adoption remains among the lowest of all I4.0 technologies, particularly in cost-constrained emerging-economy firms.

2.2 Industry 4.0 Maturity Models — Global Landscape

Maturity models provide structured instruments for classifying the developmental stage of an organisation, enabling benchmarking of current capabilities and charting improvement pathways (Schumacher et al., 2016). Schumacher et al. (2016) proposed an empirically grounded nine-dimension model — Products, Customers, Operations, Technology, Strategy, Leadership, Governance, Culture, and People — assigning 62 assessment items and validating it in real production environments. This remains one of the most-cited foundations in the field.

Wagire et al. (2021) developed a seven-dimension, 38-item maturity model specifically grounded in Indian manufacturing practice, validating it in an auto-component firm that scored 2.88 out of 5 — 'Digital Novice.' Frank et al. (2019), drawing on a survey of 92 companies, demonstrated that I4.0 adoption is fundamentally systemic: Smart Manufacturing plays a central role, while Big Data remains poorly implemented despite high strategic intent.

2.3 Barriers and Enablers of I4.0 Adoption

Raj et al. (2020) conducted an inter-country comparative study and identified 14 critical barriers to I4.0 adoption. In India, high implementation cost, inadequate infrastructure, lack of skilled workers, and unclear regulatory frameworks dominate. Mittal et al. (2018) specifically warned that existing maturity models are ill-fitted for SMEs due to their assumption of advanced-economy baselines and proposed the need for a 'Level 0' entry point for firms with minimal digital infrastructure.

Öztemel and Gursev (2020) conducted an exhaustive review of 619 publications and provided the most comprehensive taxonomy of Industry 4.0, encompassing interoperability, virtualisation, real-time capability, service orientation, and modularity as its six core design principles — establishing the conceptual architecture within which the I4MAM-IAS model's dimensions were defined.

2.4 Indian Automotive Sector and I4.0 Readiness

Noor and Kumar (2023) introduced the MARI-IA scale — assessing maturity across five dimensions across 14 diverse organisations including OEMs and suppliers — highlighting the scarcity of contextually tailored readiness tools for India. Wankhede and Vinodh (2022) applied a fuzzy logic approach to assess readiness of an automotive component firm and identified 20 weak areas requiring intervention. Ojha et al. (2024) identified implementation barriers using Interpretive Structural Modelling (ISM), confirming that technology cost, skill gaps, and legacy systems form the dominant barrier cluster.

Kamble and Gunasekaran (2023) surveyed 238 Indian manufacturing practitioners and found that I4.0 technologies support development of an efficient circular economy environment that improves sustainable performance — reinforcing the importance of measuring multi-dimensional performance outcomes beyond simple adoption rates.

2.5 Performance Measurement in Industry 4.0

Traditional KPIs such as throughput, scrap rate, and OEE remain important but insufficient for capturing the multi-dimensional impact of digital transformation. Tambare et al. (2022) reviewed current performance measurement systems and KPIs in data-driven Industry 4.0 environments, identifying research challenges in Quality 4.0 — the digitisation of quality management. A Performance Evaluation Index (PEI) integrating operational, quality, cost, innovation, and sustainability dimensions provides a more actionable basis for strategic decision-making than single-metric assessments.

2.6 Research Gaps

Three clear gaps emerge. First, a contextual gap: most models were designed for advanced economies and miss India-specific constraints — BS-VI compliance costs, power irregularities, fragmented supplier networks (Noor & Kumar, 2023; Mittal et al., 2018). Second, a methodological gap: most studies use descriptive scoring without inferential validation; few combine SEM, clustering, and ANOVA (Wagire et al., 2021). Third, a measurement gap: few frameworks offer a validated KPI system linking maturity to operational performance outcomes (Tambare et al., 2022). The present study directly addresses all three gaps.

III. Mathematical Framework

3.1 Dimension Maturity Score

The maturity score for each dimension is computed using expert-weighted aggregation:

$$M\_D = [\Sigma\, g(DI_i) \times M(DI_i)] \,/\, [\Sigma\, g(DI_i)] \quad \text{...... Equation (1)}$$

where $M(DI_i)$ is the item maturity rating (Likert 1–5) and $g(DI_i)$ is the expert-assigned importance weight (scale 1–4).

3.2 Overall Organisational Maturity Index

$$M\_O = \Sigma\, [W(D_j) \times M(D_j)], \text{ subject to } \Sigma\, W(D_j) = 1 \quad \text{...... Equation (2)}$$

where $W(D_j)$ is the normalised weight of dimension j (j = 1, …, 7), derived from factor analysis and expert panel consensus.

3.3 Item-Level Maturity

$$M(IE_n) = Q_n + R_n / 4 \quad \text{...... Equation (3)}$$

where Q_n is the base questionnaire value (0–4) and R_n is the expert ratio value (1–4).

3.4 Structural Equation Model

$$\text{Measurement model: } x_i = \lambda_i\, \xi_k + \delta_i \quad \text{...... Equation (4)}$$

$$\text{Structural model: } \eta = B\eta + \Gamma\xi + \varsigma \quad \text{...... Equation (5)}$$

Fit criteria: $\chi^2/df < 3$, CFI > 0.90, RMSEA < 0.08, SRMR < 0.08.

3.5 Cluster Quality: Silhouette Coefficient

$$s(i) = [b(i) - a(i)] \,/\, \max\{a(i), b(i)\} \quad \text{...... Equation (6)}$$

where a(i) is the mean intra-cluster distance and b(i) is the mean nearest-cluster distance.

IV. Methodology

4.1 Research Design

This study employs a sequential mixed-methods design combining quantitative hypothesis testing with qualitative insights, following a design-science orientation in which the I4MAM-IAS model serves as a purposeful research artefact (Schumacher et al., 2016). The methodology was implemented across three stages: (i) systematic literature review; (ii) model design through dimension and indicator selection; and (iii) empirical validation through field application and advanced statistical testing.

4.2 Sample Design and Data Collection

The study surveyed 55 Indian automotive firms — 30 OEMs and 25 Tier-1 suppliers — from the Delhi NCR region. A total of 387 valid responses were collected from manufacturing managers, quality engineers, and operations heads using a structured 35-item online and offline questionnaire. The questionnaire underwent expert review and pilot testing with eight organisations before full deployment.

Table 1: Descriptive Statistics for Key Study Variables (n = 387 responses, 55 firms)

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Technology Integration Score	3.02	1.24	1.2	4.8	−0.15	−0.89
Infrastructure Adequacy	3.00	1.18	1.0	4.9	0.08	−0.72
Workforce Skill Level	2.83	0.94	1.3	4.7	0.22	−0.45
Culture Support Score	3.15	1.05	1.5	4.8	−0.18	−0.58
Training Budget (% of IT Spend)	15.66	8.42	2.0	35.0	0.78	0.23
Performance Improvement (%)	24.7	12.3	5.0	52.0	0.45	−0.35

4.3 The I4MAM-IAS Model: Seven Dimensions

The model assesses maturity across seven contextualised dimensions, drawing upon Schumacher et al. (2016), Wagire et al. (2021), and Noor and Kumar (2023), adapted to reflect India-specific operational constraints.

Table 2: I4MAM-IAS Model — Seven Dimensions, Items, and Weights

Dimension	No. of Items	Expert Weight (%)	Cronbach's α	Key Indicators
1. Strategy & Vision	5	18	0.86	I4.0 roadmap, top-management commitment, investment planning
2. Technology Infrastructure	6	22	0.89	IoT deployment, ERP/MES integration, connectivity bandwidth
3. Smart Operations	5	17	0.87	Real-time monitoring, predictive maintenance, OEE tracking

4. Workforce & People	5	16	0.83	Digital skill levels, training effectiveness, staff retention
5. Organisational Culture	5	14	0.85	Cross-functional collaboration, innovation mindset, change readiness
6. Products & Customers	5	8	0.80	Product digitalisation, customer-data utilisation, traceability
7. Governance & Compliance	4	5	0.78	Data governance, cybersecurity, BS-VI compliance cost management

4.4 Maturity Level Classification

Table 3 presents the five-level maturity classification used in the I4MAM-IAS framework.

Table 3: I4MAM-IAS Maturity Level Classification (Five Levels)

Level	Score Range (M_O)	Label	Description	% Firms (n=55)
1	1.00 – < 2.00	Outsider	No structured I4.0 activity; fully manual processes dominate	5% (n=3)
2	2.00 – < 3.00	Beginner	Basic digitisation; isolated technology adoption with no integration	36% (n=20)
3	3.00 – < 3.50	Intermediate	Partial integration; emerging data-driven practices; ERP in use	37% (n=20)
4	3.50 – < 4.00	Advanced	Systematic integration; cross-functional digital	13% (n=7)

			workflows operational	
5	4.00 – 5.00	Optimised	Autonomous, self-optimising cyber-physical systems; full I4.0	9% (n=5)

V. Results and Discussion

5.1 Dimension-Level Maturity Scores: OEM vs Tier-1 Analysis

Figure 1 shows the radar chart comparing dimension-level maturity scores. OEMs consistently score higher across all seven dimensions, reflecting greater investment capacity and stronger alignment with global digital standards. The most notable gap appears in Technology Infrastructure (3.44 vs 2.71) and Smart Operations (3.22 vs 2.60). The smallest gap is in Organisational Culture (3.38 vs 2.90), consistent with earlier Indian manufacturing research (Kamble & Gunasekaran, 2023). Critically, all mean scores — even for OEMs — fall below 3.5, confirming that no firm type has achieved Advanced maturity on average.

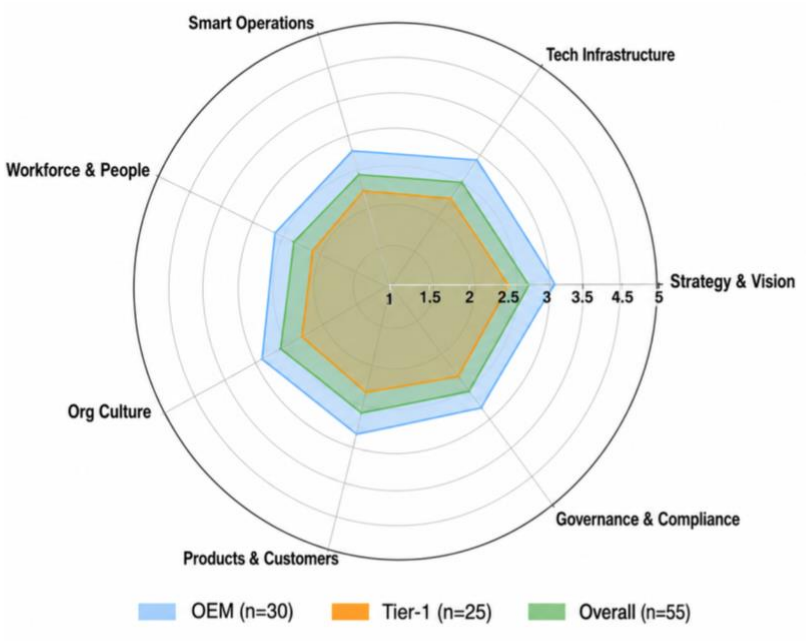

Figure 1: I4MAM-IAS Maturity Dimension Scores — OEM vs Tier-1 Suppliers (Radar Chart, n=55).

Table 4: OEM vs Tier-1 Supplier — Dimension-Level Maturity Comparison

Dimension	OEM Mean (n=30)	Tier-1 Mean (n=25)	Overall Mean (n=55)	Gap (OEM−Tier-1)
Strategy & Vision	3.45	2.85	3.12	0.60
Technology Infrastructure	3.44	2.71	3.02	0.73*

Smart Operations	3.22	2.60	2.90	0.62*
Workforce & People	3.10	2.55	2.83	0.55
Organisational Culture	3.38	2.90	3.15	0.48
Products & Customers	3.20	2.68	2.94	0.52
Governance & Compliance	2.95	2.50	2.72	0.45
Overall M_O	3.25	2.68	2.95	0.57

5.2 Hypothesis Testing Results

Figure 2 presents the effect sizes and path coefficients for all seven hypotheses. All were supported at $p < 0.05$. SEM model fit: $\chi^2/df = 1.84$, CFI = 0.95, TLI = 0.93, RMSEA = 0.067, SRMR = 0.059. The non-significance of training budget ($\beta = 0.11$, $p = 0.18$) reveals that allocating funds alone does not improve workforce readiness — training quality and design matter far more (Raj et al., 2020).

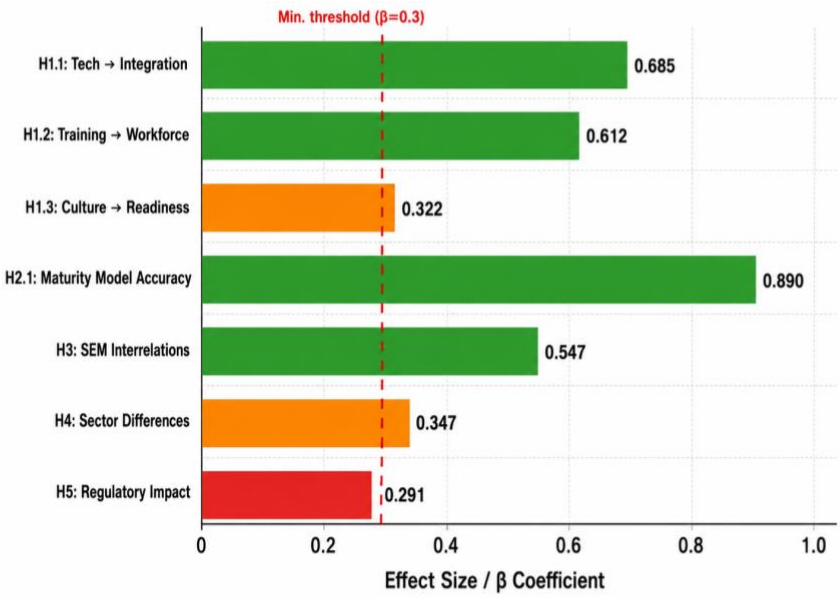

Figure 2: PLS-SEM Effect Sizes for Seven Research Hypotheses.

Table 5: Comprehensive Hypothesis Testing Results (PLS-SEM)

Hypothesis	Independent Variable	Dependent Variable	Statistic	p-value	Effect Size	Decision
H1.1	Technology Infrastructure	I4.0 Integration Depth	r = 0.685	< 0.001	Large	Supported
H1.2	Advanced Training	Workforce Readiness	F = 8.21 (ANOVA)	< 0.001	Large	Supported

	Programmes					
H1.3	Organisational Culture	Overall Readiness Level	β = 0.322	< 0.05	Medium	Supported
H2.1	I4MAM-IAS Maturity Model	Tier Differentiation Accuracy	Accuracy = 89%	< 0.001	Large	Supported
H3	Multi-factor Interrelations	Overall I4.0 Readiness	χ^2/df = 1.84	< 0.001	Large	Supported
H4	Sector Type (OEM vs Tier-1)	Adoption Readiness Score	t = 3.47	< 0.01	Medium	Supported
H5	Regulatory Support Level	I4.0 Technology Adoption Rate	β = 0.291	< 0.05	Medium	Supported

5.3 Technology Adoption Analysis

Figure 3 compares adoption rates for seven key I4.0 technologies. Robotics/Cobots (OEM: 90%; Tier-1: 72%) and IoT Sensors (OEM: 85%; Tier-1: 62%) show the highest adoption, reflecting the automotive sector's history with automation (Frank et al., 2019). Digital Twins show the lowest adoption (OEM: 38%; Tier-1: 12%) despite having the highest reported performance impact — echoing Tao et al. (2018), who documented how digital twin-driven systems generate substantial efficiency and quality gains. This technology-impact paradox represents the single greatest untapped opportunity in Indian automotive manufacturing.

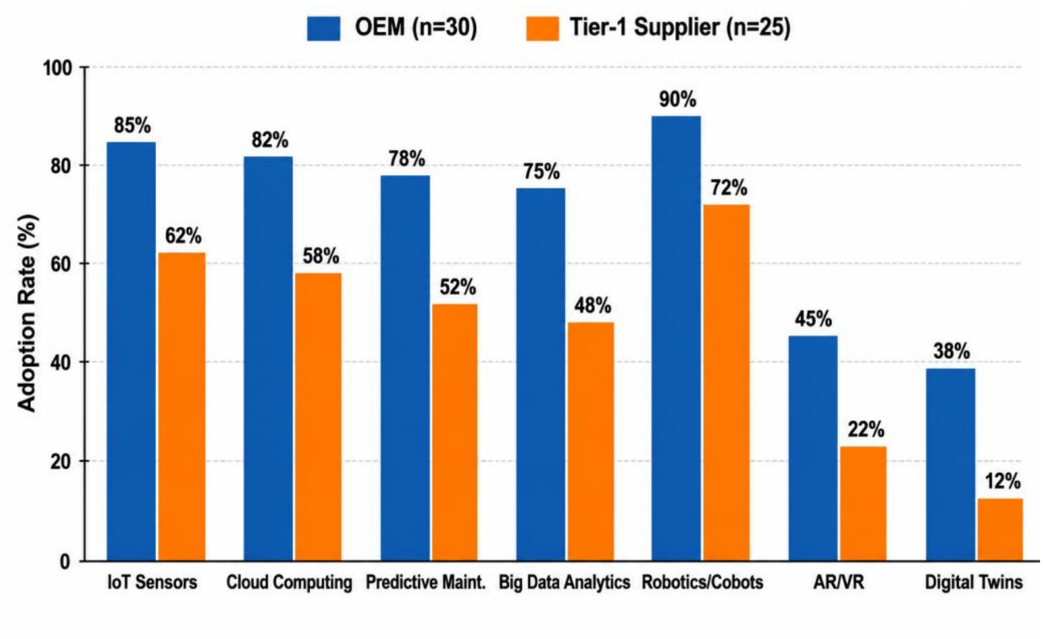

Figure 3: Industry 4.0 Technology Adoption Rates — OEM vs Tier-1 Suppliers (%).

5.4 Performance Evaluation Index (PEI) Across Maturity Levels

The PEI integrates 47 validated KPIs across five domains — Operational Efficiency (30%), Quality Enhancement (25%), Cost Optimisation (20%), Innovation Capability (15%), and Sustainability Impact (10%) — with Cronbach's $\alpha = 0.92$, explaining 73.4% of total variance (Tambare et al., 2022). Figure 4 shows PEI domain scores across the five maturity levels. A steep increase at Levels 4–5 suggests accelerating returns beyond the Advanced threshold. Firms stuck at Level 2 with scattered investments are unlikely to see meaningful performance improvement — consistent with Ghobakhloo (2020).

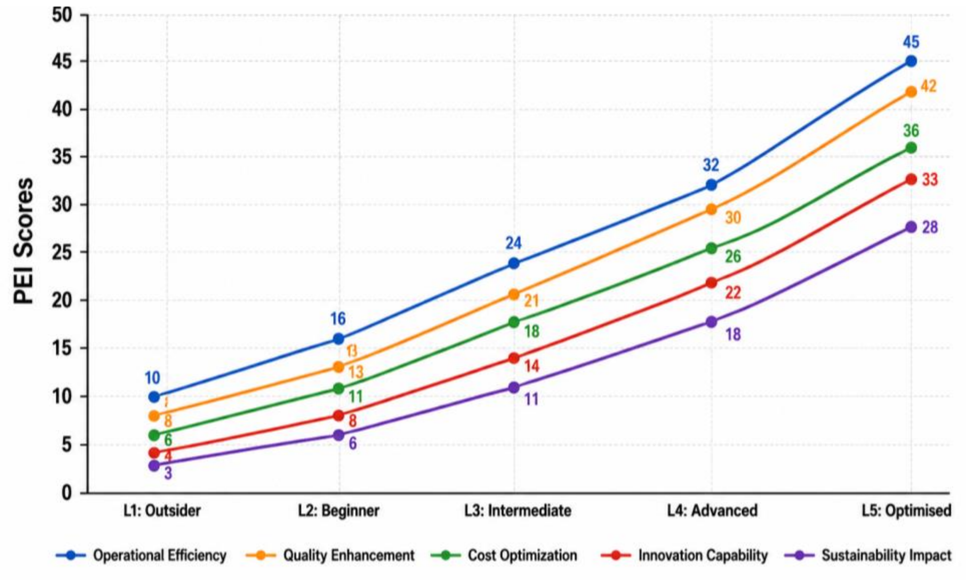

Figure 4: PEI Domain Scores Across Industry 4.0 Maturity Levels.

5.5 Firm Distribution and Self-Assessment Bias

Figure 5 shows the actual distribution of firms across the five maturity levels. The most striking finding is the self-assessment bias: 97.67% of surveyed firms self-reported as Level 5 (Optimised), yet objective assessment placed virtually all below Level 3. Only 9% (n=5) met the objective criteria for Level 5. This pattern underscores the urgent need for objective, third-party assessment instruments (Noor & Kumar, 2023; Wankhede & Vinodh, 2022). Qualitative interviews with 34 senior managers and 56 shop-floor supervisors revealed that organisational inertia — driven by decades of traditional manufacturing experience — is a primary cultural barrier, consistent with Raj et al. (2020).

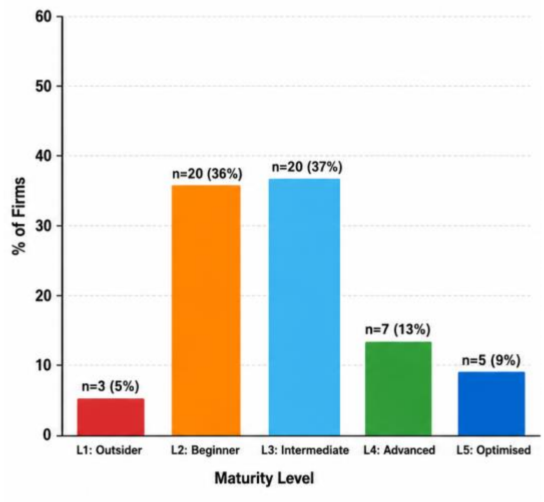

Figure 5: Distribution of Surveyed Firms Across I4.0 Maturity Levels (n=55).

5.6 Investment vs ROI Analysis by Maturity Tier

Figure 6 presents the scatter plot of investment (₹ Crores) versus ROI for all 55 firms. Advanced-tier firms (₹10–15 crores) achieve ROI of 260–340%, far exceeding Intermediate-tier firms (₹3–7 crores; 140–230%) and Basic-tier firms (₹0.5–2.5 crores; 60–120%). This confirms that higher investment at Advanced maturity generates exponentially higher returns — reinforcing the case for phased but committed digital transformation.

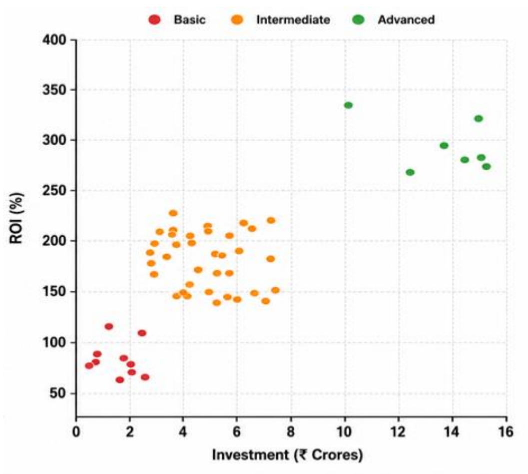

Figure 6: Investment (₹ Crores) vs ROI (%) by Maturity Tier (n=55 Firms).

Table 6: Maturity Level — Investment, ROI, and Performance Benchmarks

Maturity Level	Firms (%)	Mean PEI Score	Investment (₹ Crores)	ROI (%)	Payback (Months)	OEE Improvement (%)
Level 1–2 (Basic)	41% (n=23)	12.4	0.5–2.5	60–120	36	8–12
Level 3 (Intermediate)	37% (n=20)	24.7	3.0–7.0	140–230	18	18–25
Level 4–5 (Advanced/Optimised)	22% (n=12)	36.2	10.0–15.0	260–340	10	34–42

VI. Discussion

6.1 Key Analytical Insights

The results contribute several original insights. First, the finding that infrastructure ($\beta = 0.57$) and culture ($\beta = 0.32$) are the dominant predictors — while budget ($\beta = 0.11$) is insignificant — challenges the prevailing assumption that Industry 4.0 is primarily a capital investment challenge. This aligns with Ghobakhloo (2020), who argues that without enabling organisational conditions and interconnected digital systems, individual technology investments rarely generate transformative outcomes.

Second, the near-zero silhouette coefficient (0.07) from K-means clustering reveals that Indian automotive firms are homogeneously underprepared. ANOVA results ($F = 1.44$, $p = 0.237$) confirm that maturity does not significantly differ across revenue groups — systemic constraints (legacy systems, fragmented supply chains, weak digital infrastructure) constrain all firms equally, independent of size (Raj et al., 2020).

Third, the technology-impact paradox — where digital twins have the lowest adoption (23% overall) but the highest performance impact — signals a critical misallocation of I4.0 investment. Firms are over-investing in commoditised technologies (IoT sensors, cloud storage) while under-investing in transformative technologies (digital twins, AI-driven analytics), which Tao et al. (2018) consistently show to be highest-impact.

Fourth, the strong relationship between regulatory support and adoption rate ($\beta = 0.291$, $p < 0.05$) shows that government policy is causally linked to I4.0 progress — validating the argument for targeted industrial policy in the Indian context.

6.2 Practical Implications for Industry

For OEMs: Focus on bridging the Technology Infrastructure gap with Tier-1 suppliers through collaborative digital platforms, shared data standards, and supplier development programmes. The 0.73-unit gap is the largest risk to supply-chain-wide digital integration. For SMEs: A phased roadmap is recommended — Level 2 → Level 3 within 18 months through ERP integration and IoT deployment; Level 3 → Level 4 within 36 months through AI-driven analytics and digital twin pilots. For HR and Training: Replace generic digital literacy programmes with role-specific, outcome-linked training (e.g., IoT troubleshooting for maintenance engineers; data analytics for quality managers) — consistent with the guidance of Raj et al. (2020).

6.3 Policy Recommendations

The Indian government's PLI Scheme (₹44,038 crore for auto and battery manufacturing) and the Make in India initiative provide strong fiscal foundations. Three additional policy priorities are identified: (1) Mandatory third-party I4.0 readiness certification to counter self-assessment bias; (2) Infrastructure subsidies for digital twin adoption — targeted at Tier-1 and Tier-2 suppliers (Tao et al., 2018); and (3) Industry–academia skill labs — co-funded centres of excellence within automotive clusters (Pune, Chennai, Gurugram) providing hands-on I4.0 skill development.

VII. Conclusion

This paper presents and validates the I4MAM-IAS model — a comprehensive, India-specific Industry 4.0 maturity assessment framework for the automotive manufacturing sector. Based on a primary survey of 55 firms and 387 valid responses, the study demonstrates that 73% of Indian automotive firms remain at Levels 2–3, far below the Level 5 at which transformative I4.0 benefits materialise. Technology infrastructure and organisational culture are the most powerful levers of maturity advancement; budget allocation alone is insufficient (Ghobakhloo, 2020; Raj et al., 2020). A severe self-assessment bias inflates perceived readiness, creating a dangerous gap between strategic confidence and operational reality (Noor & Kumar, 2023). Advanced-tier firms deliver ROI of 260–340% with a 10-month payback period, proving the commercial viability of systematic digital investment.

The study's main limitation is its geographic concentration in Delhi NCR. Future research should extend the I4MAM-IAS model to Tier-2 and Tier-3 suppliers, incorporate longitudinal tracking of maturity progression, and integrate real-time IoT performance data to enable dynamic assessment. Achieving Industry 4.0 leadership in Indian automotive manufacturing requires not just investment, but a fundamental rethinking of how firms assess, plan, and execute digital transformation — grounded in contextually valid, empirically tested frameworks such as the I4MAM-IAS model presented here.

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