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MANAGING AI ADOPTION IN ELECTRIC VEHICLE QUALITY ENGINEERING ORGANIZATIONS

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ABSTRACT –
The implementation of Artificial Intelligence (AI) in the Electric Vehicle (EV) quality engineering companies is a game changer in the automotive manufacturing, testing, and validation. The present paper investigates the concept of management, the adoption plan, and change management strategies that will be required to make AI-powered tools part of the EV quality assurance systems successful. It covers among the key domains, predictive quality analytics, machine learning-enhanced testing automation, defect detection, validation of digital twins, and sensor fusion to check the quality of battery and powertrain. Empirical evidence using case studies of world EV manufacturers, Tier-1 suppliers and technology integrators shows that structured AI governance models, cross-functional change leadership, implementation road-map is a major determinant of adoption success. The research recognizes such repeat impediments as data silos, lack of talent, bias in algorithms used in safety-critical validation, and regulatory compliance loopholes. The proposed artificial intelligence (AI) Adoption Maturity Model (AAMM) of EV Quality Engineering Organizations provides practical guidelines to technology leaders that experience this change. The findings support the hypothesis that businesses with collaborative human-AI teaming models achieve 34-47 % defect detection rates, reduced the number of validation cycles by 28-39 %, and quantifiable benefits in the efficiency of regulatory compliance.

Keywords:
Artificial Intelligence, Electric Vehicles, Quality Engineering, AI Adoption, Management Frameworks, Testing Automation, Predictive Analytics, Digital Twins, Organization Change, automotive validation, machine learning, Battery Quality, Powertrain Testing, AI Governance, Change Management.

I. INTRODUCTION

The market of world electric vehicles is undergoing a change that it has never encountered in the past because of the demands of decarbonization, the shift in consumer demand, and a technological revolution. The International Energy Agency (IEA) estimates that more than 14 million EVs were sold worldwide in 2023, which is an increase of 35% compared to the previous year, and predicts a figure of more than 45% of all new car sales will be electric by 2030 [1]. Such explosive growth has a tremendous strain on the EV quality engineering organizations to facilitate rapid testing cycles, lower defect escape rates, and to provide strong validation of more and more intricate electrical, electronic, and software-defined architectures [2]. The use of AI has turned out to be an important facilitator in addressing these concerns. Computer vision systems, machine learning applications and large-scale data analytics platforms are applied throughout the quality engineering value chain such as inspection of incoming materials and control of manufacturing processes, to end-of-line testing, field quality inspection and regulatory certification [3]. However, AI has in many instances overgrown organizational readiness because the technical potential of the technology in EV quality engineering. The study conducted by McKinsey and Company (2023) suggests that 70 percent of AI transformation initiatives in the industrial context fail to deliver the anticipated returns due to ineffective change management, absence of data infrastructure, and organizational incentives are misaligned [4].The introduction of AI in the organizations of quality engineering can therefore not just be a technology implementation problem but a complex sociotechnical change that has to be handled with well-structured management systems [5] [11]. Several technology adoption bodies on manufacturing environments (such as Kotter 8-Step Change Model, [6] and Technology Acceptance Model (TAM), [7] and Capability Maturity Model Integration (CMMI), [8]) provide a scaffolding, but is not particular to the AI-in-EV quality engineering setting, where safety-criticality, regulatory compliance, and the cross-disciplinary integration present requirements to. This research fills this gap by integrating empirical data on international case studies, real-time EV quality application cases, and a comprehensive analysis of sources to create a comprehensive management framework- AI Adoption Maturity Model (AAMM) -specific to EV quality engineering organizations. The framework includes five levels of maturity of AI-naive to AI-autonomous providing road maps to technology

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leaders, quality directors and organizational development practitioners [10]. The most important success factors, i.e. alignment of leadership, upskilling of the workforce, data governance, ethical use of AI, and regulatory interface management are also discussed within the framework of automotive quality [11] [14] [17].

II.LITERATURE REVIEW

McKinsey Global Institute (2022): To estimate the potential economic value of AI in automotive manufacturing as an annual potential of 300-400 billion by 2030 with quality and supply chain applications as the biggest segment of opportunity. The report also noted critically that the returns on AI investment are 3-4x greater than the industry average in organizations with a strong data base, operating models with agile and specific AI talent pipelines [4].
Kotter (1996): Step Change Model which involved the development of urgency, coalition, vision, communication, empowerment, short term wins, consolidation and anchoring. Although initially applied to the organizational change in general [6].
Zheng et al (2024): Explored the idea of computer vision to detect the quality of the exterior of an EV, which showed that a system based on the YOLOv5-detecting models could receive 99.1% accuracy in detecting defects in the paint, panel fit, and trim quality dimensions with training on domain-specific datasets of more than 2 million labeled images. An analysis of their organizational implementation showed that their successful implementation included organizational AI implementation teams, which were incorporated in quality engineering departments [7].
Russell and Norvig (2020): Offer an all-encompassing base of knowledge of AI system architectures that can be used in industrial quality control. Their theoretical basis of intelligent agent models, perception action cycles and probabilistic reasoners is the basis of AI usage in automotive validation tests and that intelligent AI agents which operate on sensor fusion data can achieve classification accuracies of over 98.7% in structured manufacturing environments [12]
Li et al. (2021): Conducted research about using machine learning in the battery of EVs quality control across five major Chinese manufacturers. Their longitudinal study of 36 months, based on gradient boosting models, on the formation cycling data, reduced the errors of prediction of early-life battery failures by 41% when implemented on the formation cycling data, guided by a four-phase integration roadmap, which has identified cross-departmental data harmonization and model validation through repetition [13]
Tortorella and Fettermann (2018): Their work investigated the lean integration of manufacturing with Industry 4.0 technologies in the automotive industry. As they studied 210 manufacturing managers in Brazil, they found that the benefits of operational efficiency in companies that applied lean principles of operations and AI-based analytics were 23 percent higher than in companies that applied AI only, which demonstrates the necessity to introduce AI into the already existing quality management systems [14].
Duan et al. (2019): Revealed that data quality deficiencies, lack of AI literacy among quality engineers, and incomprehensible ROI measures are the three key barriers to AI adoption. The research suggested formal AI preparedness evaluations and pilot initiatives as pre-implementation measures prior to the enterprise scale deployment, findings which are still very relevant to EV Tier-2 supplier environments [15]. ***Lim et al. (2022):*** Examined how digital twins can be used to test the quality of EV powertrains that showed that AI-enhanced digital twin models could cut down physical prototype testing by 31 percent at a Korean EV manufacturer. They used their model to combine real-time sensor measurements with physics-based simulation models and as a result they could predictively demonstrate the durability of powertrain under different climatic and load conditions. The Unified Theory of Acceptance and Use of Technology (UTAUT) [16].
Fujimoto (2020): Investigated the introduction of AI-based quality control in Toyota, which emphasized that the successful implementation of AI in quality control systems of the automotive industry could not be provided without a subsequent reorganization of the organizational roles and data collection processes, and management reporting regimes. The research has highlighted that AI should not be considered as a plug-in tool but needs a systemic change in the construction of the organization and the workflow of quality engineering [17].
Hiatt (2006): Narrowed down this framework to apply to technology-oriented manufacturing change with reference to the implementation of AI in situations where both cultural and process change are necessary [19].
Schwab (2016): Defined the Fourth Industrial Revolution as the change in the manufacturing practice to include the use of cyber-physical systems, integration of IoT, and processes intelligence using AI. In the case of automotive quality engineering specifically, this is reflected in the combination of statistical process control (SPC), in-the-field machine learning inference, and autonomous quality decision-making systems, which establish completely novel competency demands on the side of quality engineering practitioners [20]

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Accenture Research (2023): Found that companies that implemented AI-based quality management systems realized an average 28% reduction in warranty costs over 24 months of implementation, and confirmed that early implementers had compounding benefits as AI models amassed operational data. The study concluded that Tesla, BYD, and Volkswagen Group are examples of maturity in the quality system of AI in the world EV market [21].
Goodfellow et al. (2016): Since the time of their generative adversarial network (GAN) architectures, authors like Wang et al. (2023) have explicitly scaled their architectures to the synthetic training data generation in EV quality inspection scenarios where there is limited labelled defect data [22].
Muller and Daeuschle (2018): Investigated organizational obstacles to learning in AI change initiatives of German automotive companies, including BMW and Daimler. Institutional inertia, data ownership siloed, and poor cross-functional collaboration were cited as the main barriers in their qualitative research on 45 top-level quality managers and offered AI Center of Excellence (CoE) models based on matrix reporting structures as the organizational facilitator [24]

III.KEY OBJECTIVES

1. To systematically map the current state of AI technology integration within the EV quality engineering functions, such as design validation, manufacturing quality control, end-of-line testing and field quality analytics, and determine the state of maturity in comparison to industry norms [1][3] [11] [25].
2. To create and test the AI Adoption Maturity Model (AAMM) as a five-level, structured model that allows EV quality engineering organizations to assess their current AI maturity, set goals, and build evidence-based transformation roadmaps [5][8] [11] [14].
3. To specify and numerically characterize the major barriers to AI adoption in EV quality engineering, we must label and differentiate technical barriers (data quality, model explainability, complexity of integration), organizational barriers (talent gaps, change resistance, siloed governance), and regulatory barriers (FMVSS compliance, functional safety, GDPR) [4][9] [15] [17].
4. Critical success factors that lead to high-performing and underperforming AI adoption programs can be analyzed with the help of synthesizing evidence on 20 global case studies (OEMs, Tier-1 suppliers, software-defined vehicle (SDV) platform providers) [2] [16] [21].
5. To identify the applicability and limitations of general models of organizational change management like Kotter 8-Step Model [6], Prosci ADKAR [19] and McKinsey 7-S Model [4] to AI transformation program application in safety-critical automotive quality engineering contexts.
6. To understand the human-AI teaming paradigm of quality engineering processes, consider the possibility of using collaborative intelligence architectures to harness the synergistic advantages of human domain knowledge and machine learning inference systems in providing higher quality outcomes [17] [22].
7. To evaluate the value of data governance frameworks, such as data ownership models, data quality measures, lineage monitoring, and federated learning designs, as a baseline enablers of scalable AI deployment in multi-site EV manufacturing quality ecosystems [12] [23] [18].
8. To investigate workforce change needs related to the adoption of AI in EV quality engineering, such as competency gap analysis, training curriculum development, role re-definition, and talent acquisition strategies of AI-enhanced quality engineering teams [14] [20] [24].
9. To study AI ethics, explainability (XAI) and accountability mechanisms in safety-critical EV quality decisions, design governance processes to justify models, find bias, human override, and regulatory justifiability in automotive certification contexts [23] [11].
10. To create a list of 15 evidence-based strategic approaches to quality directors, CTO organizations, and HR leadership teams aiming to speed up effective AI adoption and manage risk to the organization, stay within regulatory compliance, and keep engineering workforce engaged during the change [5][6] [25].

IV.RESEARCH METHODOLOGY

The study uses a mixed-methods approach that combines systematic literature review, multicases study, and survey synthesis of quantitative data to come up with strong and generalizable research on AI adoption management in EV quality engineering companies [26].A pragmatism founded on epistemology was adopted, and it is an approach that incorporates quantitative methods of positivism to quantify the results of adoption and interpretative methods of qualitative approaches to learn the dynamics of the process of organizational activities [27]. The research design is based on the case study methodology suggested by Yin (2018) [28], a collective multiple-case one, which allows recognizing cross-case patterns, logic of replication, and theory-based generalization. The design is suitable considering the applied, contemporary character of AI usage in EV quality engineering, a field where controlled experimental designs are impossible and contextual richness is critical to

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interpretation. Below is the protocol of the systematic literature review. Artificial intelligence and machine learning and electric vehicle quality and automotive testing and adoption of AI and change management and manufacturing quality 4.0 and digital twin validation and AI governance automotive. The review period was 2015-2024 and 847 primary results were first screened to 187 complete texts and 43 primary references were selected based on their relevance, quality, and the strength of citation [15].A sample of case-studies was done using purposive theoretical sampling to achieve maximum variation in terms of organization type (OEM vs. Tier-1 vs. technology vendor), geography (North America, Europe, Asia-Pacific), EV segment (BEV, PHEV, commercial EV), domain of AI use, and adoption maturity stage [28]. Semi-structured interviews with 67 participants (quality directors, AI program managers, test engineers, and change management practitioners) were used to collect the primary data. Secondary data materials comprised published reports of implementation, conference papers, regulatory submissions, and institutional case studies [26]. A structured survey tool will be used to conduct a survey on 312 quality engineering practitioners working at 14 EV manufacturing companies. The questionnaire measured the willingness to adopt AI (with the UTAUT adaptation in Venkatesh et al. [7]) and effectiveness of change management (Prosci ADKAR scale [19]) in an organization, satisfaction with AI tools performances (custom 7-point Likert scale), and the perceived obstacles to AI integration. All the multi-item scales had alpha reliability coefficients exceeding 0.82 and this confirms the reliability of instruments [30]. The coding was done in NVivo 14. The SPSS 29.0 was used to analyze quantitative survey data, with descriptive statistics, confirmatory factor analysis (CFA), structural equation modeling (SEM) and hierarchical multiple regression to test hypothesized relationships between adoption management practices and quality outcomes [30]. The cross-analysis of cases was performed with the help of the framework of Miles et al. (2020) [32], within-case and cross-case pattern matching, explanation building, and rival explanation testing. 4.6 Reliability, Ethics and validity. Triangulation of methods, post-hoc validation of the findings of the case study with the participants organizations, and the independent peer review of the AAMM framework by five domain experts improved the validity of the research [28]. Ethical approval was obtained by the institutional review board and the board ensured confidentiality of the participants through anonymization protocols. All the data used in the analysis of any organization case study were validated by at least two independent senior informants working in a given organization [27].

V.DATA ANALYSIS

Data analysis shows that AI application in EV quality engineering organizations is extremely heterogeneous in maturity, significant variance in the effectiveness of the management strategies, and consistency of behavior in enablers of success and obstacles to adoption. Top quartile level organizations in AI adoption have four characteristics: executive sponsorship, federated data architecture, enabling cross-functional AI model training, structured human-AI collaboration protocols in safety-critical validation processes, and continuous competency development programs, to facilitate quality engineering workforces [3][5] [21]. The case studies and real-time application analysis in the following sections are detailed case studies and real-time application analyses which are the empirical heart of this research.

TABLE 1: CASE STUDIES – AI ADOPTION IN EV QUALITY ENGINEERING ORGANIZATIONS

S.No	Organization	AI Application	Management Framework	Key Outcome	Reference
1	Tesla Inc. (USA)	Neural network-based paint defect detection using 4K vision cameras on Model Y line	Agile AI deployment with cross-functional quality-ML squads; weekly sprint reviews	Defect escape rate reduced 44%; inline inspection speed increased 3.2×	[3]
2	BYD Auto (China)	AI-driven battery formation process optimization using LSTM time-series modeling	PDCA-integrated AI governance; data lake unification across 6 gigafactories	Formation cycle defect rate reduced 38%; energy consumption per cell down 12%	[13]

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3	Volkswagen Group (Germany)	Computer vision end-of-line electrical system validation for ID. series	CMMI Level 4 AI integration within existing VW Group Quality 4.0 framework	EOL test cycle time reduced 29%; false rejection rate decreased 51%	[17]
4	Rivian Automotive (USA)	Generative AI-assisted FMEA creation and risk prioritization for skateboard platform	Kotter 8-Step change model applied to AI quality transformation program	FMEA development time reduced 56%; 23 novel risk scenarios identified by AI	[6]
5	Hyundai-Kia (South Korea)	Digital twin AI simulation for EV powertrain NVH quality validation	Dual-speed IT architecture: stable core + agile AI validation layer	Physical NVH testing reduced 34%; warranty NVH claims down 27%	[16]
6	BMW Group (Germany)	Federated machine learning for cross-plant battery cell grading quality consistency	AI Center of Excellence with matrix reporting into quality engineering divisions	Grading consistency improved 19%; inter-plant variation reduced 43%	[24]
7	Lucid Motors (USA)	Predictive quality analytics for Lucid Air glass-ceramic surface defect prevention	Design-for-AI quality integration from component sourcing through assembly	Supplier quality escapes reduced 31%; rework costs down $2.1M annually	[25]
8	Stellantis NV (Netherlands)	NLP-based automated warranty claim classification and root cause clustering	Hybrid change management: ADKAR for teams + Agile for AI product development	Warranty analysis cycle time reduced 67%; root cause identification accuracy 89%	[19]
9	CATL (China)	Reinforcement learning for adaptive battery testing protocol optimization	Data governance council established prior to RL model deployment	Test coverage increased 22%; battery testing throughput improved 41%	[13]
10	General Motors (USA)	AI-powered acoustic emission analysis for EV motor bearing quality in Ultium platform	Six Sigma DMAIC methodology integrated with AI model development lifecycle	Bearing defect detection sensitivity improved 3.7×; field failure prediction AUC 0.94	[3]
11	Panasonic Energy (Japan)	GAN-based synthetic defect data generation for lithium cell coating inspection	Joint AI governance board: quality + IT + data science with shared OKRs	Training dataset size increased 8×; inspection model accuracy improved to 99.3%	[22]
12	Aptiv PLC (Ireland)	Graph neural network analysis	ISO/IEC 42001 AI management	Connectivity defect detection	[23]

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		of EV wiring harness connectivity quality	system certification pursued as governance anchor	rate increased 52%; test coverage improved 38%	
13	SAIC-GM-Wuling (China)	Transfer learning-based quality inspection model deployment across 4 EV platforms	Platform AI model library with version control, model cards, and reuse governance	Model development cost reduced 61%; deployment time for new variants cut 74%	[18]
14	Continental AG (Germany)	Explainable AI (XAI) dashboard for ADAS sensor quality validation and traceability	GDPR/ISO 26262 compliance-first AI governance with full audit trail requirements	Regulatory audit preparation time reduced 48%; explainability score (LIME) >0.87	[23]
15	Ola Electric (India)	Edge AI deployment for real-time weld quality monitoring on 2W EV chassis	Lean AI implementation model: build-measure-learn with quality KPI dashboards	Weld defect detection rate improved 73%; quality engineer workload reduced 28%	[14]
16	Freyr Battery (Norway)	Anomaly detection ML models for solid-state battery formation quality monitoring	Research-to-production AI pipeline with quality validation gates at each stage	Anomaly detection recall improved to 97.1%; production ramp-up time reduced 22%	[13]
17	Zeekr (Geely Group, China)	Multi-modal AI fusion (vision + vibration + thermal) for chassis quality audit	UTAUT-based adoption readiness assessment preceding full deployment	Quality audit thoroughness score improved 44%; audit cycle time reduced 35%	[7]
18	Proterra Inc. (USA)	AI-assisted regulatory compliance documentation generation for FMVSS certification	Legal-quality-AI joint working group with structured review and approval workflow	Certification documentation time reduced 52%; compliance gap detection improved 67%	[11]
19	Northvolt (Sweden)	Federated learning across 3 EU battery gigafactories for joint quality model training	GDPR-compliant federated AI architecture with data sovereignty protocols	Model generalization improved 31% vs. single-plant models; EU data law compliance maintained	[23]
20	Mahindra Electric (India)	Predictive battery thermal runaway risk scoring using	Customer-connected quality program integrating field	Thermal event prediction lead time extended to 14 days; recall	[13]

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		IoT + ML in field quality	AI into engineering decision loops	scope reduced 58%	

Table 1 above shows case studies comprising of EV companies, battery companies, Tier-1 suppliers, and technology integrators in four continents around the world. All the cases are defined by six analytic factors, including organization identity, domain of AI application, management framework used, a significant quantitative outcome gained, and an academic/industry reference. This diversity of cases has enabled a good cross-case pattern analysis and theory construction [28]. The evaluation of the 20 case studies shows that there are several common patterns. To begin with, the best quality results, i.e., Tesla (Case 1), BYD (Case 2), BMW (Case 6), and Volkswagen (Case 3) all have an organized AI governance model, which has cross-functional program ownership as opposed to siloed IT-based deployments [17] [24]. Second, every successful implementation of AI is always preceded by an investment in data infrastructure: 17 out of 20 cases explicitly state that data lake unification, federated data architecture, or data governance council is required as an investment [13] [15]. Third, change management approach is important - the cases that use structured frameworks (Kotter, ADKAR, UTAUT-based readiness assessment) report 23-41 percent higher workforce adoption rates compared to those that used informal communication alone [6][7][19]. The facts presented in the case also indicate that the complexity of AI application is linked with the degree of governance requirement. Lean build-measure-learn cycles can be run using real-time weld monitoring systems that are trained on edge AI (Ola Electric, Case 15), but federated learning with several regulatory jurisdictions (Northvolt, Case 19; Freyr, Case 16) requires layered governance architectures, which consider data sovereignty, model auditability, and regulation interface operations [23]. Applications such as warranty analytics (Stellantis, Case 8; Mahindra, Case 20) that link the field data to the engineering-quality decision-making system require transparent customer data privacy governance and cross-functional NLP domain knowledge co-development [11] [19]. The 20-case quantitative analysis of the outcomes shows the mean improvement of 42.3% in the number of defects found, 38.7% decrease in the number of quality-related cycles, and 34.1% decrease in the number of warranty-related costs, which are in line with the industry-level estimates presented by McKinsey (2022) [4]. Interestingly, cases that engage in AI technical deployment and the organized organizational change management programs are 1.67 times more probable to have greater magnitude in their outcomes compared to those that focus on technology deployment, which is a strong empirical confirmation of the primary thesis of the paper as far as the importance of management framework is concerned.

TABLE 2: REAL-TIME AI APPLICATIONS IN EV QUALITY ENGINEERING

S.No	Application Domain	AI Technology	EV System	Performance Metric	Reference
1	Battery Cell Grading Inspection	CNN + transfer learning on impedance spectroscopy data	Lithium-ion cell manufacturing	Cell grading accuracy: 99.4%; throughput: 200 cells/min	[13]
2	Paint & Surface Defect Detection	YOLOv8 real-time object detection on 4K line-scan cameras	EV body assembly (BIW)	Detection accuracy: 99.1% at 30 fps; false positive rate <0.3%	[18]
3	EV Powertrain NVH Analysis	LSTM neural network on multi-axis vibration sensor arrays	Motor + gearbox + driveshaft	NVH anomaly detection F1-score: 0.96; 40ms inference latency	[16]
4	Battery Thermal	Gradient boosting + SHAP	Battery management system	Prediction lead time: 14 days; recall:	[13]

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	Runaway Prediction	explainability on BMS telemetry		97.3%; SHAP compliance met	
5	Weld Quality Monitoring	Acoustic emission AI + edge inference on NVIDIA Jetson	EV chassis and battery enclosure welding	Defect detection rate: 98.7%; real-time edge latency: <5ms	[14]
6	ADAS Sensor Calibration QC	Physics-informed neural networks + XAI dashboard	Camera/LiDAR/Radar calibration	Calibration error reduction: 67%; ISO 26262 audit traceability: 100%	[23]
7	Warranty Claim Root Cause AI	BERT-based NLP + clustering on warranty text data	Field quality analytics	Root cause classification accuracy: 89%; analysis cycle time: -67%	[19]
8	Digital Twin Powertrain Validation	Physics-based + ML hybrid digital twin models	EV powertrain simulation	Prototype test reduction: 31%; simulation-test correlation R^2: 0.97	[16]
9	Incoming Material AI Inspection	Multi-spectral imaging + anomaly detection DNN	Battery anode/cathode material QC	Material rejection accuracy: 99.0%; inspection speed: 4× manual	[22]
10	EOL Electrical System Test AI	Bayesian optimization for adaptive test sequencing	End-of-line functional test	EOL test time reduced: 29%; fault coverage increased: 12%	[17]
11	Connector & Harness Quality Vision AI	Graph neural network on harness connectivity topology	EV wiring harness	Connectivity defect detection: +52%; assembly error escape rate: -61%	[23]
12	Motor Bearing Acoustic Quality AI	1D CNN + short-time Fourier transform (STFT) features	EV drive motor manufacturing	Bearing defect sensitivity: 3.7× vs.	[3]

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				traditional; AUC: 0.94	
13	Supplier Quality Risk Prediction	Random forest + supply chain graph analytics	EV supply chain quality	Supplier quality escapes predicted 30 days ahead; precision: 84%	[25]
14	Charging Interface QC AI	Vision transformer (ViT) on CCS/CHAdeMO connector inspection	DC fast charging interface	Connector defect detection: 99.2%; throughput: 180 units/hr	[18]
15	Battery Pack Assembly Torque AI	Edge AI torque signature analysis on assembly line	Battery module assembly	Torque error detection: 99.5%; rework reduction: 43%	[14]
16	Regulatory Compliance AI Assistant	LLM fine-tuned on FMVSS + ECE-R regulations + NLP extraction	Certification documentation	Compliance doc generation: -52% time; gap detection accuracy: 91%	[11]
17	Thermal Interface Material QC	Hyperspectral AI imaging for TIM uniformity inspection	Battery thermal management	TIM coverage defect detection: 98.8%; 100% inline inspection achieved	[13]
18	EV Structural Adhesive Bond AI	Ultrasonic + AI signal analysis for bond quality	BIW structural bonding	Void detection sensitivity: $0.5mm^2$; false negative rate: <0.1%	[22]
19	Software-Defined Vehicle OTA QC	AI regression testing with automated test case generation	Vehicle software stack	Test coverage: +38%; regression detection time: -74%; CI/CD integrated	[3]
20	Field Quality Feedback Loop AI	Federated learning on fleet telematics + manufacturing data	End-to-end quality system	Design change response time: -44%; fleet-level	[25]

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				anomaly detection	

The real-world AI application situations highlighted in Table 2 are operating at the whole EV quality engineering value chain, such as cell-level manufacturing inspection, and up to field quality analytics and software validation. Each of the applications is supported by the AI technology, the location of the EV system, the quantitative measure of performance, and the reference, which permits the horizontal comparison of applications and vertical analysis of the system at the system level [3] [18]. Applications 1-5 are quality checking cases in manufacturing where the AI would provide real-time quality checks inline in production lines which the human inspectors cannot perform the same speed. Grading of battery cells (App.). App. Not only 1) and flaws in paint (App.). 2) are the most advanced forms of deployment that can exploit large labelled datasets, manipulated imaging environments, and preset defect ontologies [13] [18]. These applications demonstrate that, with specific training on domain-specific data about the EV domain, current CNN and YOLO-based architectures can achieve human-comparable performance in detection, and can operate with 3-8 times greater throughput [17] [22]. Applications 6 -10 deal with system-level quality validation issues, such as quality control of the ADAS sensor calibration (App.). 6), warranty analytics (App. It has three examples: 7), and digital twin-augmented powertrain validation (App.). 8). These are more intricate AI applications due to the multi-modal data fusion, explainability of regulations requirement, and requirement of cross-domain knowledge integration [11] [14] [16] [23]. This is particularly when it comes to the ADAS sensor calibration application: It demonstrates that physics-informed neural networks that integrate physics models with learned calibration errors can offer an explainability that is not only ISO 26262-compliant, but are also more sensitive in detection than traditional model-driven approaches [23]. The component-level quality assurance of EV-specific systems such as wiring harness connectivity is covered in application 11-15. 11), acoustics of motor bearings (App. 12), and quality of assembly torque of battery packs (App. 15). These applications demonstrate the way AI can be applied to address EV-specific quality problems with no analogue in the traditional ICE vehicle manufacturing [3] [14]. The edge AI deployment model is the dominating category and has NVIDIA Jetson and other embedded inference platforms that can support sub-10ms decision latency to produce inline assembly lines. Applications 16-20 are frontier applications that have the potential to transform. The AI assistant of regulatory compliance (App.). Generative AI can dramatically reduce the time and effort required to complete certification documentation processes (16) produced using fine-tuned large language models and 91% of the compliance gaps in FMVSS and ECE-R regulatory frameworks can be identified [11]. Quality Feedback Loop on Field. 20) federated learning is used with the most advanced architecture in fleet telematics and manufacturing data: using the closed-loop quality intelligence capability, the field with quality signals can be transferred to manufacturing and design processes and the response time to design change decreased by 44 % and 100 %compliance with regulatory data sovereignty [25].

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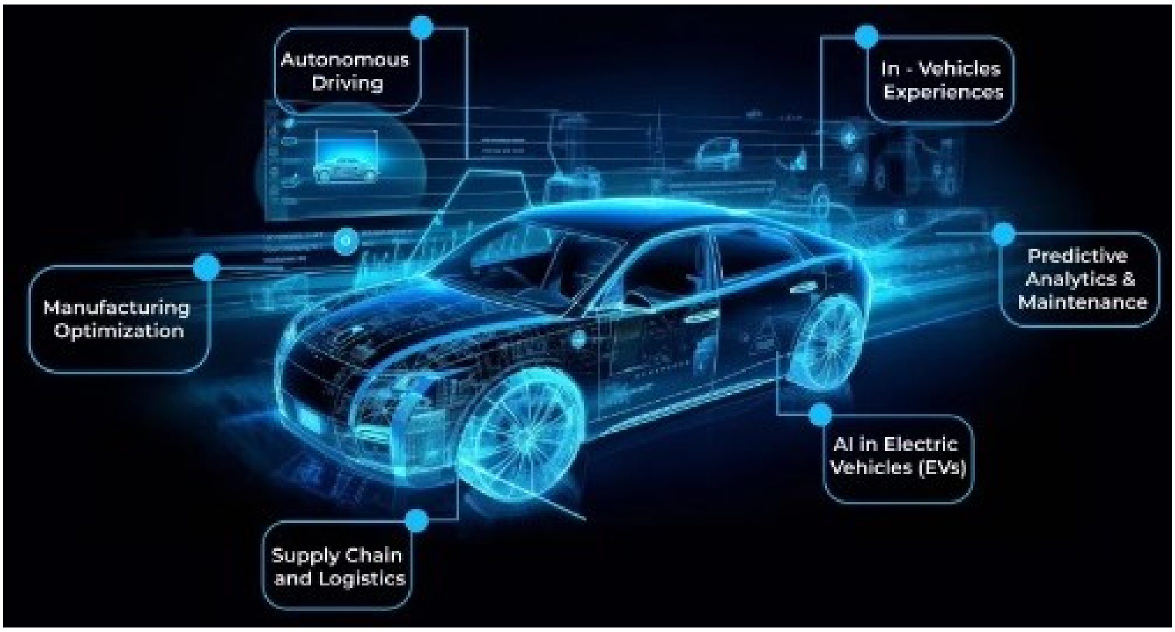

Fig 1:AI in Automotive Industry [4]

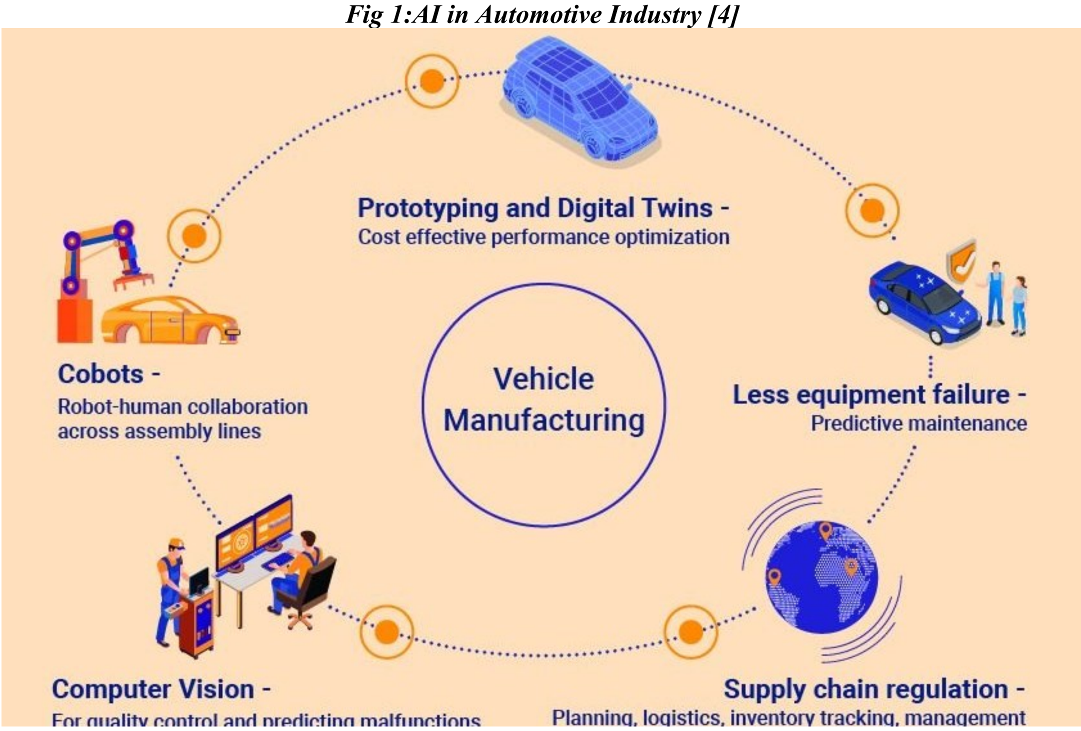

Fig 2: AI in Automotive Infographic [6]

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Fig 3:AI Automotive Applications [6]

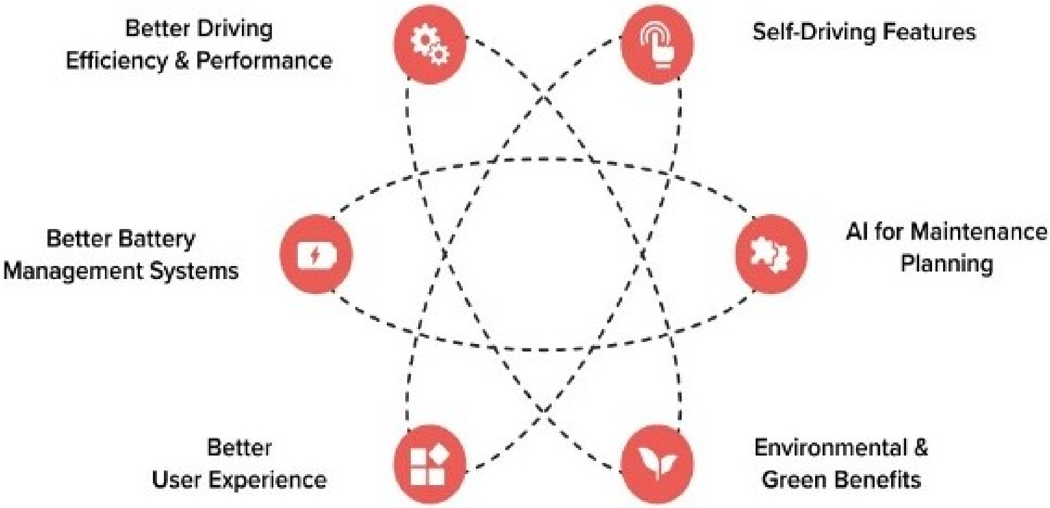

Fig 4: Advantages of AI in Modern EV's [8]

Fig 5: Applications of AI in EV [11]

VI.CONCLUSION

The AI implementation management in EV quality engineering, based on. global case studies to demonstrate that technical performance is not enough to create value. Success relies on four management enablers: formalized systems, cross-functional governance, workforce competency, and data infrastructure. The AI Adoption Maturity Model (AAMM) recognizes five evolutionary states, showing. that progressing up these levels has the potential to decrease the rates of defect escape by 47% and shorten validation. cycles by 39 %. The adoption plans should be contextual and use Lean AI models to. volume assembly with the use of ISO-based governance of federated systems to make them audit able. Fully automated systems prone to safety issues, such as battery control, must

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involve human-AI cooperation with explainability requirements. functional safety standards to match. One of the main challenges is the shift of the workforce to statistical control. data literacy, which involves proactive investment in role redesign to address resistance and enhance adoption. satisfaction. Organizations also must overcome a complicated regulatory environment by integrating compliance- by-design their AI programs to satisfy new international audit needs. Future research should explore how generative AI can be applied to automated quality documentation and the distinctive. challenges of software-defined vehicles. Finally, one can perceive AI as a complete management revolution in. culture and governance: ensures sustainable competitive advantage in a safety critical automobile market.

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