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Research Article

Leveraging Generative AI to Build Custom Engineering Apps in PLM Ecosystems

Rukmini Kumar Sreeperambuduru
Anna University, India

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ABSTRACT

PLM (Product Lifecycle Management) systems customarily represent a highly rigid, monolithic Systems-of-Record for engineering and product-related data. The emergence of Generative AI-powered Low-Code/No-Code development platforms presents a transformative opportunity to evolve these legacy architectures into adaptive Platforms of Apps specifically designed for Digital Twin implementations. This architectural transition enables domain experts—including mechanical engineers, quality specialists, and production managers—to create purpose-built micro-applications such as geometric dimensioning and tolerancing validation tools, first article inspection apps, corrective action tracking systems, Overall Equipment Effectiveness dashboards, and predictive maintenance solutions without requiring formal programming expertise. The Platform of Apps model separates core data management functions from application-layer innovations, establishing PLM as a foundational services infrastructure upon which diverse engineering applications can be rapidly developed and deployed. By integrating real-time data synchronization, machine learning-based predictive analytics, and prescriptive maintenance recommendations, organizations can transform passive data repositories into active optimization engines. This paradigm shift addresses critical integration challenges in traditional PLM deployments while establishing technical foundations for comprehensive Digital Twin architectures in regulated manufacturing environments.

Keywords: Product Lifecycle Management, Digital Twin, Low-Code No-Code Platforms, Generative Artificial Intelligence, Smart Manufacturing

1. Introduction

PLM (Product Lifecycle Management) systems have served as the authoritative enterprise backbone for engineering data governance, configuration management, and cross-discipline collaboration throughout the product development lifecycle for more than 30 years. PLM systems have provided organizations with version-controlled documentation, advanced management of complex bill-of-materials hierarchy, and formalized change management processes across distributed global engineering enterprises in many industries. Emerging Industry 4.0 themes such as cyber-physical production systems, Industrial Internet of Things deployments, and real-time operations analytics have fundamentally challenged the architectural assumptions behind most conventional PLM implementations.

The subject of the size of the enterprise can be considered as a major issue for integrating Industry 4.0 technologies into the PLM ecosystem. According to research on 24,000 companies, 6% of micro firms, 18.4% of small firms, 35.5% of medium firms, and 47.1% of large firms utilize Industry 4.0 technologies [1]. This sizable gap between actual and desired performance indicates that enterprise-wide PLM models are insufficient for the new networked and variously mature manufacturing ecosystem, with 63% of early adopting firms expecting quality and defects to improve with Industry 4.0 deployment. 46.3% expect to increase their production outputs with Industry 4.0 implementations. Therefore, fulfilling this operational requirement is a must for PLM systems [1]. Teleworking has a human resource aspect, as it is an enabler of distributed product development. Prior to the COVID-19 pandemic, teleworking was used by 1.2% of employees. By the end of the WSP, it accounted for 8.8% of employees but reached as much as 50% and 40% for employees in communications and information services and technical and scientific activities, respectively [1].

Digital transformation of enterprise systems is not restricted to manufacturing; similar issues have been identified in other sectors. In a sample of digital consumers, digital transformation constructs explained 42.2% of the variance in operational outcome constructs. Logistics and fulfillment capabilities were found to be the strongest predictors of system performance [2]. With more than 80% of users connecting to and communicating through mobile devices, the survey results imply that today's PLM ecosystem must support mobile-first access and next-generation data synchronization, which legacy architectures were not designed for [2]. The data also show that transactional convenience and post-transaction logistics capabilities are more influential on system satisfaction than informational content features, indicating that PLM platforms should focus on operational workflows instead of merely on managing static documentation [2].

Utilizing generative AI and Low-code/No-code development approaches addresses the architectural challenges as described above. It allows for domain experts, mechanical engineers, quality assurance analysts, manufacturing process engineers, and supply chain analysts to create fit-for-purpose micro-applications without needing formal programming language skills. The result is an evolution of existing rigid PLM Systems of Record to extensible Platforms of Apps and the structural and technological foundations to enable bidirectional digital threads between physical objects and their Digital Twin counterparts, while retaining data integrity and governance controls as required for regulated manufacturing environments.

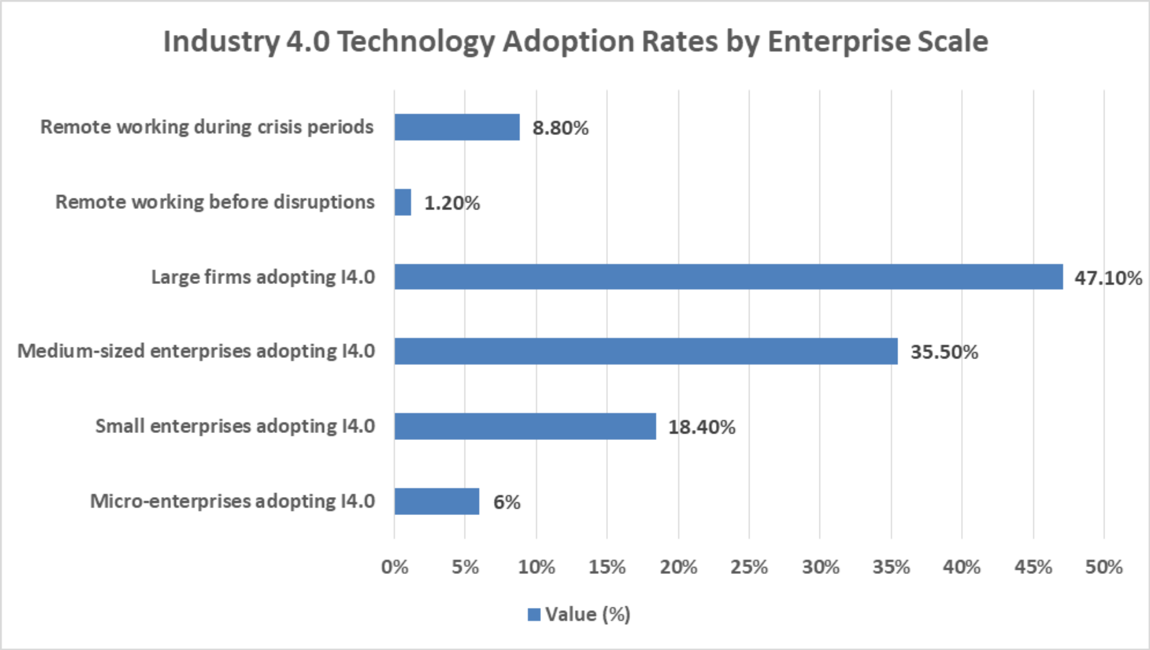

Figure 1: Industry 4.0 Technology Adoption Rates by Enterprise Scale [1, 2]

2. Limitations of Traditional PLM Architectures

2.1 Structural Rigidity

Customary PLM systems were built at a time when product lifecycles were much longer, with engineering change orders (ECOs) typically following a predictable order of approved stakeholders. As a result, most PLM systems have historically prioritized consistency and compliance over configurational flexibility. Business logic, hard-coded into the proprietary code, makes customization expensive and vendor-dependent. This lock-in and the resulting architectural rigidity put organizations behind the curve in the ability to adapt PLM environments to new manufacturing, new products, and more rapid innovation.

As in legacy PLM systems, the software development also suffers from the configuration problem. The requirements of the software products change often due to technological developments, which increases the time of software development threefold and increases the defects per function point of the software by 40%, in contrast to stable requirements [3]. This is confirmed in the replication with PLM systems, where Industry 4.0 requires the continuous adaptation of the production systems. The study also indicated that project over-budget is exacerbated by having a methodology mismatch by a factor of 189%, and project failure is exacerbated by a factor of 2.3. For major system projects, this translates to system choice-related wasted costs of $2.3 million annually [3]. Further, this research found that organizations with poor system architecture alignment had a 30-50% drop in productivity as well as a 40% increase in employee turnover, showing both financial and human capital risks to inflexibility [3].

The time dimension of responsiveness adds to the challenges, with one study of 3,234 projects in 15 industries finding that sequential approaches cause a time-to-market delay of 8.3 months, on average, when compared to more responsive approaches [3]. For PLM systems that support product development for companies in competitive markets, delays in time to market often mean a loss of market opportunity and competitive advantage.

2.2 Integration Challenges

The increasing number of domain-specific engineering software—computer-aided design tools, simulation platforms, manufacturing execution systems, enterprise resource planning modules, and supplier collaboration portals—has led to further integration challenges. According to research about data usage in discrete parts and product manufacturing companies, the existing enterprise architecture does not integrate the major organizational data sources such as Product Data Management (PDM) systems, Enterprise Resource Planning (ERP) systems, Supply Chain Management (SCM) systems, and MES into a single overall operational architecture [4]. This fragmentation causes the formation of information silos, which negatively affect data flows in Industry 4.0 implementations and Digital Twin architectures.

For instance, a quality engineer seeking to develop an automated non-conformance tracking app must navigate disconnected data sources spanning inspection records in the MES, supplier data in the SCM system, and design specifications in the PDM system. Similarly, a manufacturing process engineer attempting to create a real-time Overall Equipment Effectiveness (OEE) dashboard faces integration barriers when machine performance data resides in separate silos from production scheduling information and maintenance logs [4]. These fragmented architectures prevent the rapid development of engineering apps such as automated tolerance stack-up calculators, supplier quality scorecards, and IoT sensor monitoring dashboards that require unified data access across multiple enterprise systems.

Integration is also measurable from a quality perspective: Companies implementing systematic integration of development processes and supporting systems, compared to those implementing fragmented processes only based on culture and local practices, deliver 34% more work on time, reduce defects by 28%, and increase stakeholder satisfaction by 41% [3]. On the other hand, the absence of integrated data ecosystems leads to 40-60% higher defect density and high rework. Stage-gate or waterfall processes tend to have 35% rework in contrast with 15% for integration-centric processes [3]. This lack of integration also diverts engineering effort away from value-adding activities, prevents organizations from adopting new tools, and limits their competitiveness in a fast-changing manufacturing landscape.

Parameter	Value
Project failure rate multiplier	2.3x
Additional cost per major project	$2.3 million
Team productivity decreases	30-50%
Personnel turnover increases	40%
Time-to-market increase (months)	8.3
Rework effort for traditional approaches	35%

Table 1: Cost and Performance Penalties from Inflexible PLM Systems [3,4]

3. Generative AI-Powered Low-Code/No-Code Platforms

3.1 Democratizing Application Development

There has historically been a meaningful gap between domain experts and the software development lifecycle. Engineers with knowledge of manufacturing processes, quality control methods, and product performance characteristics must rely on IT departments and professional software developers to create software solutions that meet their needs. As a result, engineers suffer from communication overhead, requirements interpretation errors, and prioritization conflicts, delaying delivery of dedicated engineering application software. However, customary software development is exceptionally costly and time-consuming, requiring meaningful amounts of programming, testing, and debugging by specialists and incur costs related to infrastructure and maintenance (which increasingly do not meet the manufacturing industry's demand for rapid delivery, validation, and commissioning) [5].

Low-Code/No-Code development seeks to change these disadvantages by enabling the development of software with no programming experience through visual programming environments, component libraries, and drag-and-drop software interface builders. There is evidence that these products are becoming increasingly popular and are being widely adopted. The size of the low-code market in China was estimated at 3.47 billion yuan (about US$0.49 billion) in 2023. It is estimated to grow at a compound annual growth rate (CAGR) of 32.4% to reach 10.63 billion yuan (about US$1.50 billion) in 2027 [5]. The adoption of low-code technology is driven by organizations' recognition that democratized development capabilities reduce the application backlog that inhibits their digital transformation efforts. The global low-code development platform market has received wide-ranging investment attention. Forrester estimated the low-code market to be worth $3.8 billion in 2017. This is mirrored in corporate M&A activity, such as Siemens' $730 million acquisition of Mendix in October 2018 [5].

LCNC platforms can allow business users to quickly create digital applications without a software developer, allowing organizations and employers to avoid expensive software development costs and gain the benefit of having their applications developed and distributed at much faster speeds, such as weeks and days, compared to the customary software development processes, which may take months and years [6]. This has special advantages for small and medium-sized enterprises not able to afford to employ skilled programmers.

3.2 Micro-App Architecture

Micro-app design is in contrast to previous application development philosophies for enterprise software, focused on monolithic design; that is, previous approaches strove to capture all use cases in a single platform. Instead, micro-app architectures decompose functionality into discrete purpose-built applications designed for specific engineering workflows. Implementations have been shown to have a meaningful impact on productivity. In a study of low-code programming applications for manufacturing, it was found that users with no programming background were able to teach robots in 10 minutes [5].

The range of engineering micro-apps enabled by LCNC platforms spans the entire product lifecycle. In design engineering, domain experts can rapidly create geometric dimensioning and tolerancing (GD&T) validation apps that automatically check design specifications against manufacturing capabilities, or parametric design configurators that enable sales engineers to generate custom product variants based on customer requirements. Quality engineering teams can develop first article inspection (FAI) apps that guide inspectors through measurement sequences and automatically populate AS9102 forms, corrective action request (CAR) tracking apps that manage supplier non-conformances through 8D problem-solving workflows, and statistical process control (SPC) dashboards that visualize real-time Cpk indices from connected measurement devices [5]. Manufacturing engineers benefit from work instruction apps that deliver visual assembly guidance to operators on tablets, cycle time analysis tools that identify bottlenecks across production cells, and changeover optimization apps that sequence setup activities to minimize downtime.

Production processes also see dramatic productivity improvements from the use of micro-apps. For example, the lamination of a tape to a mobile phone touch screen is limited to 100 per person per hour when done manually, before a low-code programming initiative. The result of this campaign is a productivity increase of 2000 pieces of tape lamination per robot per hour (a 20-fold increase) [5]. Non-specialized workers could be brought up to speed on how to operate a production line for the product in less than an hour, and a changeover to another production line took ten minutes. The production lines did not require specialist technicians, lowering the threshold for production systems to be robotized. These platforms also typically provide governance, security, and regulatory compliance controls, which are particularly required by regulated industries, and allow for standardization and sustainable innovation at the same time [6].

4. Transitioning from System of Record to Platform of Apps

4.1 Architectural Evolution

PLM has viewed itself mainly as an integrated System of Record. Historically, implementations used centralized databases and proprietary business logic to enforce PLM functionality over a wide geographical area and multiple companies. This model provides transaction integrity, audit traceability, and access control that are required in regulated manufacturing processes, but at the expense of extensibility and customization. The other model of the architecture, the Platform of Apps model, separates the core data management functions from application layer product and service innovation and represents PLM as a foundational services platform for engineering applications.

The Platform of Apps architecture enables a diverse ecosystem of engineering applications to coexist on a unified data foundation. Product engineers can deploy configuration management apps that enforce design rules and automatically validate bill-of-materials structures against engineering standards. Reliability engineers can create failure mode and effects analysis (FMEA) apps that link design parameters to potential failure modes and automatically calculate risk priority numbers. Test engineers can build automated test sequence apps that interface with laboratory equipment, capture results, and generate compliance documentation for regulatory submissions. Supply chain engineers can develop supplier scorecard apps that aggregate quality metrics, delivery performance, and cost data to support sourcing decisions. Each of these engineering apps operates independently while drawing from and contributing to the shared PLM data repository, enabling cross-functional visibility without the integration complexity of traditional point-to-point interfaces [4].

In particular, the increasing convergence of AI capabilities across platforms is being observed. A recent study shows that the average AI integration rate in business models has quadrupled from 10% in 2019 to 30% in 2023, showing acceleration year-over-year on the road to smart application platforms [7]. That trend reflects the fact that platform-based architectures allow engineers to deploy AI-based capabilities much faster than system-level changes.

4.2 Governance and Scalability

Other governance risk categories that emerge from the democratization of application development capabilities include data governance, security and compliance, and operational risk. A study on LCNC adoption using an Extended UTAUT model shows that effort expectation makes the highest contribution to platform adoption intention with a path coefficient of 0.366, followed by performance expectation with a path coefficient of 0.265 [8]. An R^2 of 0.641 indicates that the combination of performance expectation, effort expectation, social influence, perceived risk, and perceived cost accounts for a good amount of variance in intention to adopt platform technologies [8].

These findings inform the design of governance of PLM platforms: platform interfaces should minimize effort and maximize perceived performance to encourage engineering domain experts to adopt and commit to PLM platforms. The fact that all paths were meaningful, $p<0.001$, indicates governance aspects need to be taken into account for platform adoption to be successful [8]. Successful deployments of the Platform of Apps would need to take care of persistent investment in user experience, and management of governance around ease of access with adequate security and compliance measures for a regulated manufacturing setting.

Parameter	Value
AI adoption rate (2019)	10%
AI adoption rate (2023)	30%
Effort expectation path coefficient	0.366
Performance expectation path coefficient	0.265
Variance explained (R^2 value)	0.641
Statistical significance threshold	$p<0.001$

Table 2: Platform Adoption Predictors and AI Integration Trends [7, 8]

5. Enabling Digital Twin Capabilities

5.1 Real-Time Data Integration

Digital Twins are characterized by the combination of instrumentation of physical assets, computational modeling methods, and data connectivity capabilities that enable the virtual instance to persistently remain faithful to its physical twin. In contrast to static CAD models or periodical simulation snapshots, operational digital twins have bi-directional data streams: sensor telemetry from physical assets updates their virtual models, while the latter is used to update their physical counterparts by means of optimization recommendations or control parameter adjustments. By 2026, the static twin will evolve into a more clever and data-driven system, leveraging real-time analytics, AI, data infrastructure, edge computing, generative AI, and interoperability frameworks [9].

The Platform of Apps (PoA) architecture is a collection of data connectors, protocol adapters, and pipelines that maps digital twin data to the asset instrumentation profile. Digital twins using data from sensors, edge devices, and the cloud create a real-time digital representation of the physical asset in the field. New network technologies such as 5G and 6G will enable low latencies and immediate analytics/decision loops for automation and smart grids [9]. These include timestamp synchronization in distributed sensor networks, evaluating data quality in terms of whether the measurement values are within a physically reasonable range, and correlating events in the sense of determining correlations or relationships between two sensor streams that are not otherwise synchronized.

Engineering apps that leverage real-time Digital Twin data integration span multiple operational domains. Condition monitoring apps continuously track vibration signatures, temperature profiles, and acoustic emissions from rotating equipment such as pumps, compressors, and turbines to detect early signs of bearing wear or imbalance. Energy management apps aggregate power consumption data from individual machines to visualize facility-wide energy flows, identify inefficient equipment, and recommend load-balancing strategies. Environmental compliance apps monitor emissions, effluent quality, and noise levels against regulatory thresholds and automatically generate exception reports when parameters approach limits. Asset tracking apps combine RFID, GPS, and barcode data to provide real-time visibility into the location and status of tools, fixtures, and work-in-progress throughout the manufacturing facility [9].

5.2 Predictive and Prescriptive Analytics

Another important area of Digital Twin research is the creation of predictive models that anticipate the state of the system and prescriptive models that provide recommendations. Research into data-driven digital twin (DDDT) frameworks for predictive maintenance in smart manufacturing show that the right machine learning models and digital twin architecture can yield highly accurate predictions. By evaluating the performance of seven machine learning algorithms on CNC turning, it was found that Random Forest Regressor was the most accurate in predicting the surface roughness with an R^2 value of 94.2%. An XGB Regressor yielded the best results for power consumption prediction with an R^2 value of 98.9% and a Mean Absolute Percentage Error of 3.0% [10].

The Platform of Apps architecture enables these predictive benefits to be realized quickly because engineering teams can easily compose small, focused analytics micro-applications that drill down into specific prediction requirements. Specific examples of predictive engineering apps include tool wear prediction apps for CNC machining operations that analyze cutting forces, spindle power, and acoustic emission signals to forecast remaining tool life and schedule replacements before quality degradation occurs. Surface finish prediction apps correlate process parameters such as cutting velocity, feed rate, and depth of cut with resulting surface roughness values to optimize machining conditions for high-precision components [10]. Spindle health monitoring apps track thermal expansion, vibration spectra, and bearing frequencies to predict spindle failures weeks in advance, enabling planned maintenance during scheduled downtime. Energy consumption forecasting apps model the relationship between production schedules, machine utilization patterns, and facility power demand to support energy procurement planning and demand response participation.

In the proposed digital twin architecture, 80% of the operations data will be used to train models, whilst 20% will be used to validate the accuracy of the prediction on seen and unseen data [10]. These data-driven predictive models act as smart digital twins, allowing for better decision-making and improving the quality, productivity, and sustainability of production systems. This enables the predictive maintenance of manufacturing processes due to energy savings and allows for the manufacturing of high-quality products. This allows for more sustainable and cost-efficient production, which is relevant for the development of PLM systems from data repositories to data-driven and optimization-driven systems.

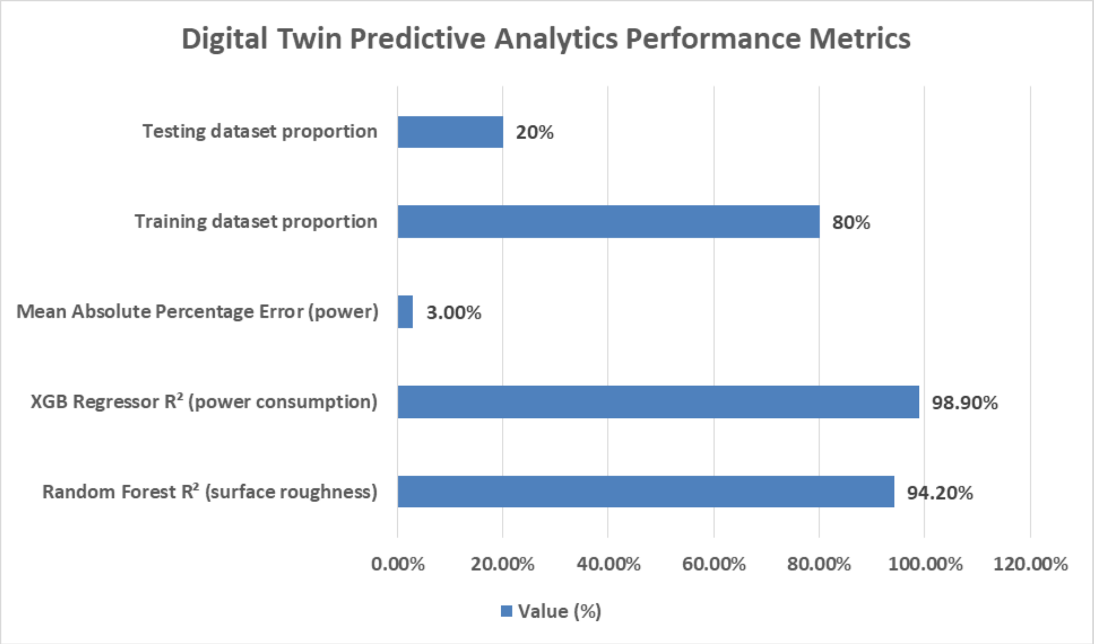

Figure 2: Digital Twin Predictive Analytics Performance Metrics [9, 10]

Conclusion

With the advent of Generative AI and Low-Code/No-Code frameworks, PLM architecture can evolve from a Systems of Record orientation to a Platforms of Apps strategy. Now manufacturing organizations can meet the challenges of agility for Industry 4.0 and a Digital Twin strategy, all on a PLM foundation. This architectural evolution democratizes application development, enabling domain experts to create specialized micro-applications—including GD&T validation tools, FMEA management systems, condition monitoring dashboards, tool wear prediction apps, and real-time OEE tracking solutions—without extensive IT involvement or programming expertise. The integration of machine learning algorithms within Digital Twin frameworks enables predictive maintenance capabilities that anticipate equipment failures, optimize process parameters, and reduce unplanned downtime through data-driven insights. Real-time synchronization between physical assets and virtual representations transforms PLM platforms from passive documentation systems into active decision-support engines capable of prescriptive recommendations. Organizations embracing this paradigm position themselves to extract full value from engineering data assets while maintaining adaptability essential for sustained innovation in competitive global manufacturing landscapes.

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