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REVIEW ARTICLE

Artificial Intelligence in SOLIDWORKS: Applications and Impacts

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ABSTRACT:

The integration of Artificial Intelligence (AI) and Machine Learning (ML) into SOLIDWORKS has profoundly transformed mechanical engineering workflows, enabling unprecedented levels of efficiency, creativity, and precision in product design. This review examines the spectrum of SOLIDWORKS' AI-driven tools, their diverse applications across engineering disciplines, and their transformative impact on the field. SOLIDWORKS 2025 introduces Aura AI, a context-aware intelligent assistant embedded directly within the CAD environment. Aura AI automates repetitive modelling tasks, generates design alternatives through generative algorithms, and delivers real-time regulatory compliance insights, thereby enabling engineers to concentrate their cognitive resources on higher-order innovation activities. Empirical evidence suggests that AI-mediated automation reduces routine task burdens sufficiently to allow engineers to dedicate approximately 40% more of their working time to creative problem-solving. However, the indispensable role of human oversight in validating AI-generated outputs remains critically acknowledged. Looking forward, SOLIDWORKS continues to pursue expanded industry-specific AI customization, with particular emphasis on aerospace and medical device sectors, while advancing predictive maintenance algorithms through the incorporation of Internet of Things (IoT) sensor data. This convergence strategically positions SOLIDWORKS as a leading platform in smart manufacturing, driving technological innovation while simultaneously affirming the irreplaceable value of domain engineering expertise.

KEYWORDS: SOLIDWORKS; Digital Manufacturing; Artificial Intelligence; Industry 4.0; Machine Learning; Generative Design.

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1. INTRODUCTION

The rapid evolution of Artificial Intelligence (AI) and its confluence with computer-aided design (CAD) platforms marks one of the most consequential technological developments in contemporary engineering practice. Over the past decade, AI — encompassing subfields such as machine learning (ML), deep learning, natural language processing (NLP), and computer vision — has progressively migrated from research laboratories into industrial design environments, reshaping how engineers conceptualize, model, simulate, and optimize physical products.

SOLIDWORKS, developed by Dassault Systèmes and widely regarded as one of the world's leading

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parametric CAD platforms, serves as a compelling case study for this technological convergence. Deployed across more than 2.9 million licensed seats globally as of 2024, SOLIDWORKS underpins product development pipelines in sectors ranging from consumer electronics and automotive engineering to aerospace, biomedical devices, and industrial machinery [1]. The introduction of AI capabilities into this well-established ecosystem represents a paradigm shift: rather than passively executing designer instructions, the CAD environment begins to anticipate, recommend, and autonomously generate design content based on learned patterns and user intent.

The theoretical underpinnings of this transformation are rooted in decades of research into machine learning [2], generative modelling [3], and topology optimization [4]. The practical realization of these concepts within a commercial CAD tool, however, demands not only algorithmic sophistication but also seamless integration with existing user workflows, design databases, and simulation frameworks. SOLIDWORKS has pursued this integration through a series of iterative software releases, culminating in the SOLIDWORKS 2025 platform with its flagship Aura AI assistant — the first fully embedded, context-aware conversational AI agent within a mainstream parametric CAD environment.

This review provides a systematic examination of the AI technologies incorporated into SOLIDWORKS, the engineering domains in which they are being applied, and the measurable impacts on design productivity, solution quality, and the nature of engineering work itself. Additionally, the review addresses the prevailing challenges limiting wider adoption and charts prospective directions for future development, drawing on published literature through mid-2025 [5,6,7]. By situating SOLIDWORKS' AI capabilities within the broader landscape of Industry 4.0 and smart manufacturing, this paper aims to serve both practising engineers seeking to understand the tools at their disposal and researchers investigating the frontier of AI-augmented engineering design.

2. AI TECHNOLOGIES IN SOLIDWORKS

2.1. Aura AI: Context-Aware Design Assistant

The most significant AI advancement introduced in SOLIDWORKS 2025 is Aura AI, a context-sensitive intelligent assistant integrated directly into the CAD ribbon and command manager interface. Unlike earlier chatbot-style assistants that operated as external overlays, Aura AI is architecturally embedded within the modelling kernel, granting it direct access to the active part tree, assembly constraints, simulation results, and material databases [8]. This tight coupling enables Aura AI to provide contextually relevant recommendations rather than generic guidance.

At its core, Aura AI employs a large language model (LLM) fine-tuned on a curated corpus of SOLIDWORKS documentation, engineering design standards, and anonymized user interaction data. The model is further augmented by a retrieval-augmented generation (RAG) architecture that queries up-to-date regulatory databases (ISO, ASME, FDA design controls) in real time, enabling on-demand compliance checking during the modelling process [9]. Engineers can interact with Aura AI using natural language queries such as: 'Create a ribbed bracket with a minimum factor of safety of 2.5 for aluminium 6061-T6 under a 500 N axial load', and the assistant will generate an initial parametric model, run a preliminary FEA check, and propose geometry modifications to satisfy the specified constraint.

Aura AI also incorporates intent prediction capabilities, analysing the sequence of modelling commands issued by a designer to anticipate the next likely operation. This predictive modelling reduces the cognitive overhead associated with navigating complex command menus and has been reported to reduce average feature-creation time by approximately 30% in internal Dassault Systèmes usability studies. Furthermore, Aura AI supports design version history analysis, enabling engineers to query why a specific design decision was made in

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prior sessions and to explore alternative parametric paths without losing the established design intent.

2.2. Generative Design and AI-Driven Shape Synthesis

Generative design represents one of the most transformative AI applications in CAD, enabling the automated exploration of vast solution spaces defined by engineering constraints and performance objectives. In SOLIDWORKS, generative design capabilities interface with the SIMULIA topology study and the xDesign cloud-based modelling environment, wherein AI algorithms — primarily density-based methods such as SIMP (Solid Isotropic Material with Penalization) augmented by gradient-free neural network surrogates — iteratively redistribute material within a design envelope to minimize mass or compliance while satisfying specified load cases and manufacturing constraints [4,10].

Regenwetter et al. [3] conducted a comprehensive review of deep generative models in engineering design, demonstrating that variational autoencoders (VAEs) and generative adversarial networks (GANs) can effectively learn the latent design space of mechanical components from training datasets and generate novel geometries with predicted superior performance. These approaches, when integrated within SOLIDWORKS' parametric framework, allow engineers to specify performance targets and receive multiple distinct design alternatives ranked by manufacturability, estimated cost, and structural performance — a capability that fundamentally changes the role of the engineer from drafter to design director.

The neural surrogate modelling approach is particularly valuable for computationally expensive multiphysics simulations. Rather than performing full finite element analyses for each candidate design during optimization, the AI surrogate — trained on a library of previously computed FEA results — predicts structural responses (stress, deformation, natural frequency) with sufficient accuracy to guide the generative search, reserving high-fidelity FEA for final design validation [11]. This strategy can reduce total computational time for a topology optimization study by one to two orders of magnitude, making the process feasible within typical industrial design cycle timeframes.

2.3. AI-Augmented Simulation and Finite Element Analysis

SOLIDWORKS Simulation, the integrated FEA module, has incorporated several AI-assisted features in recent releases that enhance both the efficiency and accessibility of structural, thermal, and fluid analysis. Mesh intelligence algorithms, trained on thousands of component geometries and their associated mesh quality metrics, automatically recommend element sizes and refinement zones for complex geometrical features such as fillets, thin-walled sections, and contact regions — areas traditionally requiring significant analyst expertise to mesh correctly [12].

AI-driven material recommendation has also been implemented: when a designer specifies operating conditions (temperature range, applied load magnitude, corrosive environment), the system queries a materials knowledge graph trained on the ASM Alloy Center database and published materials datasheets to recommend candidate materials ranked by suitability, cost, and sustainability metrics. This capability is particularly valuable in the early design phase when material selection has the greatest leverage on downstream performance and cost [13].

Furthermore, physics-informed neural networks (PINNs) are beginning to complement conventional FEA solvers within the SOLIDWORKS ecosystem, particularly for problems involving highly nonlinear material behaviour, large deformations, and coupled thermomechanical loading — scenarios where conventional implicit FEA solvers are computationally prohibitive. Abueidda et al. [14] demonstrated the effectiveness of deep learning approaches for predicting plasticity and thermo-viscoplastic material responses, providing a pathway

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for their integration into commercial simulation environments.

2.4. Predictive Maintenance Integration via IoT and Digital Twins

SOLIDWORKS' strategic integration with the 3DEXPERIENCE platform enables a bidirectional data flow between the digital design model and physical manufacturing and operational assets. IoT sensors embedded in manufactured products — capturing vibration signatures, temperature profiles, load histories, and oil quality metrics — transmit operational data to cloud-based analytics engines that employ ML algorithms (primarily recurrent neural networks and long short-term memory, LSTM, architectures) to detect anomalous patterns indicative of impending failure [15,16]. The predicted remaining useful life (RUL) and failure mode information can then be fed back into SOLIDWORKS to guide design modifications in subsequent product iterations, closing the loop between in-service performance and design evolution.

Tao et al. [17] characterized this bidirectional feedback architecture as a defining feature of digital twin technology, wherein the virtual model and its physical counterpart co-evolve in real time. Within the SOLIDWORKS context, the digital twin manifests as a living assembly model whose constraints, material properties, and loading conditions are continuously updated to reflect the operational state of the deployed product, enabling condition-based maintenance scheduling, warranty claim root cause analysis, and field-data-driven redesign — all without requiring engineers to manually interrogate raw sensor logs.

2.5. AI-Powered Drawing Automation and Standards Compliance

The preparation of engineering drawings — a time-intensive but indispensable activity in product documentation — has been substantially accelerated by AI automation in SOLIDWORKS 2024 and 2025. Intelligent drawing views powered by computer vision algorithms can automatically identify and annotate critical features (holes, chamfers, thread specifications, surface finish requirements) based on the 3D model geometry and any pre-existing annotations in the design knowledge base [18]. The system cross-references proposed annotations against the applicable drawing standard (ISO 128, ASME Y14.5) to flag non-conforming dimensioning practices before the drawing is submitted for review.

GD&T (Geometric Dimensioning and Tolerancing) recommendation is a particularly noteworthy AI capability: based on the functional requirements specified by the engineer (mating surface, datum reference frames, assembly clearances), the AI suggests appropriate GD&T callouts and tolerance values derived from a statistical analysis of similar features in the design database. This not only accelerates the annotation process but also improves the consistency and correctness of tolerance specifications, reducing costly misinterpretations during manufacturing and inspection.

3. APPLICATIONS ACROSS ENGINEERING SECTORS

3.1. Automotive Engineering

The automotive sector represents one of the most data-rich environments for AI-augmented CAD, given the enormous volume of historical design, simulation, testing, and warranty data accumulated over decades of vehicle development. SOLIDWORKS' generative design tools have been applied to the optimization of structural automotive components — including chassis brackets, seat frames, and suspension knuckles — where simultaneous minimization of mass and compliance under multiple load cases (braking, cornering, pothole impact) is required [19]. AI-optimized components produced through topology optimization and generative design have been reported to achieve mass reductions of 20–45% relative to conventionally designed counterparts while maintaining equivalent or superior structural performance.

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Additive manufacturing compatibility checking is another AI application of high automotive relevance. As original equipment manufacturers (OEMs) and their Tier 1 suppliers increasingly adopt metal additive manufacturing (AM) for prototyping and production of complex components, SOLIDWORKS' AI tools can assess whether a generative design is printable without support structures on a specified AM platform, predict build time and material consumption, and recommend build orientation to minimize anisotropy-induced performance variability [20]. Meng et al. [21] documented the algorithmic considerations underlying the coupling of topology optimization with additive manufacturing constraints, underscoring the value of AI-mediated bridge between design freedom and manufacturing realizability.

3.2. Aerospace and Defence

Aerospace applications impose stringent demands on design tools with respect to structural integrity, fatigue life, damage tolerance, and regulatory traceability. SOLIDWORKS' AI-driven compliance checking tools are configured to flag design features that may violate FAA, EASA, or MIL-SPEC requirements during the modelling phase — a proactive approach that can substantially compress the certification timeline by identifying compliance issues before they are embedded in the design baseline [9].

In the domain of structural analysis, neural network surrogate models trained on SOLIDWORKS Simulation results for aerospace alloy components have demonstrated the ability to predict critical stress concentrations and fatigue initiation sites with mean absolute percentage errors below 5% relative to full FEA solutions, at computational speeds several hundred times faster than conventional solvers [11,14]. This speed advantage makes iterative design exploration — essential for the complex multi-objective optimization problems characteristic of aerospace structural design — practically feasible within the compressed timelines typical of defence procurement programmes.

3.3. Medical Devices and Biomedical Engineering

The medical device sector presents a uniquely challenging design environment, combining rigorous regulatory requirements (ISO 13485, FDA 21 CFR Part 820) with patient-specific customization demands and biologically driven material constraints. SOLIDWORKS' AI capabilities address these challenges through intelligent design-for-manufacturability (DfM) analysis tailored to medical-grade materials (titanium alloys, PEEK, ultra-high-molecular-weight polyethylene, cobalt-chrome), automated biocompatibility material screening, and regulatory documentation generation [1,9].

Patient-specific implant design — for orthopaedic, cranio-maxillofacial, and dental applications — has been significantly accelerated by the integration of AI-driven mesh reconstruction algorithms that convert patient CT or MRI data into parametric SOLIDWORKS models, enabling rapid customization of implant geometry to individual anatomical morphology. The AI automatically identifies bone contours, estimates cortical and cancellous bone density distributions, and proposes implant fixation strategies optimized for the specific patient's bone quality [3,22]. These capabilities reduce patient-specific implant design time from weeks to days and enable a level of anatomical fit not achievable with off-the-shelf implant libraries.

3.4. Smart Manufacturing and Industry 4.0

The alignment of AI-augmented SOLIDWORKS with the broader Industry 4.0 paradigm is most evident in the platform's integration with smart factory infrastructure. Design data generated in SOLIDWORKS can be directly transmitted to AI-enabled computer numerical control (CNC) machining centres, which use ML-based process parameter optimization to select cutting speeds, feed rates, and tool paths that maximize material removal rate while minimizing tool wear and surface

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roughness [23,24]. The design-to-manufacture data continuity eliminates manual NC programming errors and reduces process setup time.

Lee et al. [25] proposed a cyber-physical systems architecture for Industry 4.0 manufacturing that explicitly identified CAD-integrated AI as a key enabling layer, bridging the virtual design environment and the physical production floor. Within this framework, SOLIDWORKS serves as the design intelligence hub, generating not only geometric and material data but also manufacturing process plans, quality inspection programs, and assembly instructions — all enriched by AI-derived predictive analytics and optimization insights. Cloud-based collaboration enabled by the 3DEXPERIENCE platform further extends this architecture to distributed engineering teams and supply chain partners [26].

4. IMPACT ON ENGINEERING WORKFLOWS AND PRODUCTIVITY

4.1. Time Savings and Productivity Gains

Quantifying the productivity impact of AI integration in CAD is a challenging exercise, given the diversity of engineering tasks and the context-dependence of performance metrics. Nevertheless, several published assessments provide indicative data. Internal benchmarking by Dassault Systèmes and independent usability studies have reported that SOLIDWORKS' AI-assisted feature creation, drawing automation, and simulation setup tools collectively reduce total engineering design cycle time by 25–40% for medium-complexity assemblies [8]. The greatest individual time savings have been reported in drawing annotation (approximately 55% reduction) and topology optimization study setup (approximately 60% reduction), both of which historically demanded substantial manual iteration.

Beyond raw time savings, AI augmentation has been observed to shift the distribution of engineering effort toward higher-value activities. Pan and Yang [27] noted in a broader analysis of knowledge transfer in intelligent systems that automation of routine cognitive tasks consistently liberates expert practitioners to engage in more complex, creative, and judgement-intensive work — a pattern directly applicable to the SOLIDWORKS context. Engineers freed from repetitive modelling and annotation tasks report increased engagement with system-level design thinking, cross-disciplinary problem-solving, and customer-facing requirements analysis.

4.2. Design Quality and Innovation

AI-mediated design exploration has demonstrably expanded the solution space accessed by engineering teams. Generative design studies in SOLIDWORKS consistently produce geometries that human designers, constrained by intuition and time, would not independently conceive — particularly in the domain of organic, lattice-infill, and multi-material structures enabled by additive manufacturing [20,21]. Chen and Ahmed [28] demonstrated, using a deep learning generative model for airfoil design, that AI-generated design candidates exhibit higher average performance and greater diversity than human-proposed alternatives, suggesting that AI augmentation can meaningfully enhance the quality of the engineering design outcome.

Simulation-driven design, facilitated by AI surrogate models, promotes a shift from experience-based intuition to data-driven decision-making in early design phases. By enabling rapid evaluation of stress, thermal, and dynamic performance across thousands of parametric design variants, AI tools effectively democratize simulation — making high-fidelity performance assessment accessible to design engineers without specialized FEA expertise [12,13]. This democratization reduces the organizational barriers that historically separated design and analysis activities, fostering more integrated, agile, and iterative development processes.

4.3. Human Oversight and Limitations

Despite the compelling benefits documented above, it is essential to acknowledge the irreducible importance of human engineering expertise in AI-

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augmented design workflows. AI tools in SOLIDWORKS, including Aura AI and the generative design algorithms, operate within the boundaries of their training data and the constraints specified by the engineer. They are not capable of understanding unstated design intent, recognizing novel failure modes outside their training distribution, or making ethically informed trade-offs between competing stakeholder values — capacities that remain distinctly human.

Lu [29] underscored that contemporary AI systems, however powerful, function as highly capable tools for pattern recognition and optimization within well-defined problem domains — not as autonomous engineers with general reasoning capabilities. In the SOLIDWORKS context, this means that AI-generated designs must always be critically reviewed by qualified engineers, validated against applicable standards, and tested against real-world operating conditions before deployment. Blind acceptance of AI recommendations without engineering judgement constitutes a significant professional risk, particularly in safety-critical applications.

Data quality and training set representativeness pose additional limitations. AI models trained on historical design data from a particular industry or company tend to exhibit biases toward established solutions, potentially suppressing genuinely novel design approaches. Addressing this limitation requires deliberate curation of diverse training datasets and the development of AI architectures capable of extrapolating beyond their training distribution — an area of active research in both the academic and industrial AI communities [2,27].

5. CHALLENGES AND FUTURE DIRECTIONS

Several substantive challenges constrain the full realization of AI potential within SOLIDWORKS and CAD environments more broadly. Computational resource demands represent the most immediate practical barrier: generative design studies, physics-informed neural network training, and large-scale digital twin analytics require GPU-accelerated cloud computing infrastructure that may be inaccessible to small and medium-sized engineering enterprises. Dassault Systèmes has partially addressed this through the 3DEXPERIENCE Works cloud subscription model, but licensing costs and data sovereignty concerns remain points of friction for widespread adoption [26].

Interpretability and explainability of AI-generated designs present a further challenge. When a topology optimization or generative design algorithm produces a complex organic structure, engineers and certification authorities need to understand why the algorithm arrived at that solution — which physical principles it exploited, which constraints it prioritized, and where performance margins are located. Current SOLIDWORKS AI tools provide limited transparency in this regard, and the broader field of explainable AI (XAI) for engineering design remains an active and largely open research area [3,9].

Looking ahead, several promising development trajectories are identifiable. Multimodal AI interfaces — combining voice command, gesture recognition, and natural language description with conventional CAD interactions — will progressively lower the skill threshold for accessing advanced SOLIDWORKS functionality, expanding the platform's accessible user base. Federated learning architectures, wherein AI models are trained collaboratively across organizations without sharing proprietary design data, offer a pathway to building richer training datasets while preserving intellectual property confidentiality [27]. Industry-specific AI model libraries — pre-trained on sector-relevant design standards, material databases, and failure mode catalogs for aerospace, medical devices, and energy infrastructure — will further enhance the relevance and precision of AI recommendations for specialist engineering domains.

The emergence of Industry 5.0 — with its emphasis on human-robot collaboration, resilience, and sustainability alongside efficiency [30] — provides an additional philosophical frame for the future trajectory of AI in SOLIDWORKS. Rather than pursuing full design automation, the Industry 5.0 paradigm advocates for AI as an amplifier of human creativity and agency. In this vision, SOLIDWORKS' AI tools would serve as sophisticated collaborative partners: handling data processing, constraint checking, and solution generation while deferring creative direction, ethical judgement, and contextual interpretation to the human engineer.

6. CONCLUSION

The integration of Artificial Intelligence into SOLIDWORKS has fundamentally altered the landscape of computer-aided engineering design, introducing capabilities that extend far beyond the parametric modelling paradigm that defined the platform's first three decades. The principal conclusions of this review are as follows:

(1) Aura AI, introduced in SOLIDWORKS 2025, represents the first fully embedded, context-aware AI assistant in a mainstream parametric CAD environment, capable of automating feature creation, generating design alternatives, and performing real-time regulatory compliance checking within the active modelling session.

(2) AI-driven generative design and topology optimization tools enable exploration of vast solution spaces, consistently producing mass savings of 20–45% relative to conventional designs while satisfying specified structural, manufacturing, and cost constraints.

(3) Applications span a broad range of engineering sectors — automotive, aerospace, medical devices, and smart manufacturing — with AI tools delivering sector-specific value through customized material databases, regulatory compliance frameworks, and manufacturing process optimization capabilities.

(4) AI integration measurably improves engineering productivity, with reported reductions in design cycle time of 25–40%, allowing engineers to redirect effort toward higher-value creative and strategic activities. Human oversight remains an ethical and technical imperative for validating AI-generated outputs, particularly in safety-critical applications.

(5) Future development trajectories — including multimodal interfaces, federated learning, physics-informed neural networks, and Industry 5.0-aligned human-AI collaboration models — position SOLIDWORKS to continue leading the smart manufacturing paradigm while preserving the indispensable role of engineering expertise.

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