

Advancing Intelligent Toolpath Generation: A Systematic Review of CAD–CAM Integration in Industry 4.0 and 5.0

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Abstract *This systematic literature review investigates advancements in intelligent computer-aided design and computer-aided manufacturing (CAD–CAM) integration and toolpath generation, analyzing their evolution across Industry 4.0 and emerging Industry 5.0 (I5.0) paradigms. Using the theory–context–characteristics–methodology framework, the study synthesizes 51 peer-reviewed studies (from 2000 to 2025) to map theoretical foundations, industrial applications, technical innovations, and methodological trends. Findings reveal that artificial intelligence (AI) and machine learning dominate research, driving breakthroughs in feature recognition, adaptive toolpath optimization, and predictive maintenance. However, human-centric frameworks central to I5.0, such as socio-technical collaboration, remain underexplored. High-precision sectors (aerospace, biomedical) lead adoption, while small and medium enterprises (SMEs) lag due to resource constraints. Technologically, AI-driven automation and STEP-NC standards show promise, yet interoperability gaps persist due to fragmented data models and legacy systems. Methodologically, AI-based modeling prevails (49 % of studies), but experimental validation and socio-technical frameworks are sparse. Key gaps include limited real-time adaptability, insufficient AI training datasets, and slow adoption of sustainable practices. The review highlights the urgent need for standardized data exchange protocols, scalable solutions for SMEs, and human-AI collaboration models to align CAD–CAM integration with I5.0's sustainability and resilience goals. By bridging these gaps, this work provides a roadmap for advancing intelligent, human-centered manufacturing ecosystems.*

Keywords *CAD–CAM integration, Industry 4.0, Industry 5.0, toolpath optimization, AI, theory–context–characteristics–methodology (TCCM)*

Highlights

- *Artificial Intelligence drives CAD–CAM integration but lacks human-centric focus.*
- *High-precision sectors lead; SMEs face adoption barriers.*
- *Interoperability and lack of standardized AI datasets hinder progress.*
- *Review reveals the need for sustainable, scalable solutions.*

1 INTRODUCTION

The manufacturing sector has undergone radical transformation through Industry 4.0 (I4.0), characterized by cyber-physical systems (CPS), internet of things (IoT), and data-driven automation. These technologies have revolutionized production efficiency, enabling real-time monitoring, predictive maintenance, and adaptive workflows [1,2]. By integrating robotics, cloud computing, and artificial intelligence (AI), I4.0 has minimized downtime, optimized resource use and reduced operational costs [3,4].

Building on this foundation, Industry 5.0 (I5.0) emphasizes human-machine collaboration and sustainability, prioritizing ethical resource allocation and workforce upskilling alongside technological advancement [5]. This paradigm shift leverages AI not to replace human expertise, but to augment it, fostering agile, socially responsible manufacturing ecosystems [5]. Computer-aided engineering (CAE) plays a crucial role in this aspect. It enables product design validation [6], process simulation and optimization. This reduces the need for physical prototyping and minimizes costly design errors [7].

Despite the advancements in CAE and integrated design workflows, a significant disconnect often persists between computer-aided design (CAD) and computer-aided manufacturing (CAM) [8]. CAD tools focus on creating detailed, precise models, yet these models do not always seamlessly translate into manufacturable instructions for CAM systems [9,10]. This disparity can lead to communication bottlenecks, inconsistencies in toolpath generation, and rework cycles that undermine efficiency [11,12]. By improving data exchange protocols [13,14], standardizing file formats, and incorporating real-time feedback from manufacturing constraints, organizations can bridge the CAD–CAM gap and accelerate the transition from digital designs to production-ready components [11].

Various approaches have been developed to automate numerical control (NC) code generation directly from CAD models, aiming to streamline the transition from design to manufacturing. Traditional methods typically rely on geometry-based feature recognition [15] and rule-based process planning [16], wherein the system extracts manufacturing features (e.g., holes, pockets, slots) from 3-dimensional (3D) CAD geometry, maps them to corresponding machining operations, and then generates toolpaths and tool selection data. Knowledge-based systems further enhance this pipeline by incorporating predefined machining rules and best practices [17], enabling semi-automated decision-making for process parameters such as spindle speed, feed rate, and cutting depth. Post-processors then translate these planning outputs into machine-specific G-code (or equivalent) formats, ensuring compatibility with diverse computer numerical control (CNC) equipment. While these workflow-oriented techniques have significantly reduced programming time and manual intervention, they often demand expert tuning [18] and may lack flexibility when confronted with complex geometries or evolving production requirements [19]. In recent years, however, AI has begun to complement these conventional strategies, leveraging deep neural

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networks [20] and reinforcement learning (RL) [21] to automate feature recognition, optimize toolpaths, and continuously refine CAD assumptions in real time [22]. By incorporating AI modules at critical points of the CAD to CAM workflow, manufacturers can achieve adaptive, self-improving systems [23] that further streamline NC code generation and reduce the need for extensive human oversight [24], ultimately closing the design-to-production gap [25].

Recent contributions further illustrate this evolution. CAD-Coder introduces an open-source vision–language model fine-tuned to generate editable CAD code (CadQuery Python) directly from visual input [26]. Similarly, CAD-based automated G-code generation for drilling operations demonstrates an application program interface (API)-driven approach that extracts geometric parameters from CAD models and automatically generates CNC code for drilling tasks without dedicated CAM software [27]. Complementing these, the AutoCAD to G-code converter outlines a workflow for converting AutoCAD designs directly into CNC-compatible G-code [28]. Those strategies range from AI-driven CAD code generation to lightweight API-based tooling.

Despite the growing body of literature on the evolution of manufacturing technologies and the integration of AI in CAD–CAM workflows [29-31], there remains a lack of comprehensive research synthesizing the specific challenges and opportunities in bridging the CAD–CAM disconnect, particularly in the context of I4.0 and I5.0 paradigms. Recent studies have explored individual aspects, such as AI-driven NC code generation or feature recognition [32,33], yet these efforts are often narrow in scope, limited by the time span of analysis, or constrained to specific methodologies. Furthermore, the rapid adoption of human-machine collaboration and sustainable practices in I5.0 underscores the need for an updated, holistic understanding of how these advancements influence design-to-production integration. Consequently, a systematic literature review (SLR) is essential to consolidate and analyze the existing research landscape. This study proposes an SLR of over 50 studies published in the last two decades, employing the theory–context–characteristics–methodology (TCCM) framework [34], to systematically analyze critical gaps, emerging trends and understudied areas that could enhance the CAD and CAM interoperability in modern manufacturing ecosystems shaped by I4.0 and I5.0. Given this focus, the study aims to address the following research questions:

1. Theory: Which theoretical models or frameworks guide the integration of CAD and CAM in I4.0/5.0 settings?
2. Context: In which industrial or organizational contexts is CAD–CAM integration most frequently examined, and what contextual factors shape these efforts?
3. Characteristics: Which key technical or organizational features (e.g., AI-based tools, knowledge-based systems) facilitate or impede CAD–CAM interoperability, and how do they evolve under I4.0 and I5.0 paradigms?
4. Methodology: Which research methods are used to investigate CAD–CAM integration, and how do these methodological choices affect the reliability, scalability, and reproducibility of results?

2 METHODS AND MATERIALS

This section outlines the methodology employed to conduct SLR of studies addressing CAD–CAM integration within the paradigms of I4.0 and I5.0. The approach is designed to systematically identify and synthesize relevant research, ensuring a comprehensive analysis of theoretical frameworks, contextual factors, technical characteristics, and methodological trends. The TCCM framework was selected as the analytical lens due to its ability to structure multidimensional research inquiries and uncover gaps in literature. This section details the data sources, selection criteria, and analytical processes, providing sufficient information for replication and validation by other researchers.

2.1 Research Design and Analytical Framework

The SLR follows a clear, step-by-step process rooted in proven review protocols [35]. It employs the TCCM framework, delivering a well-rounded analysis of the literature while staying true to the study's goals [36]. With a spotlight on CAD–CAM integration, the review digs deepest into the Theoretical and Methodological angles, exploring how challenges are defined, tackled, and resolved. This lens sheds light on practical strategies, tools, and techniques, pinpointing overlooked areas and opening doors to fresh methodological approaches [35].

Compared to alternatives like PRISMA, which prioritize reporting transparency [37], TCCM offers a theory-driven and context-sensitive structure [36]. This is particularly valuable for research of interdisciplinary domains like CAD–CAM integration, where solutions depend on synergies between theoretical foundations, contextual constraints (e.g., industry-specific requirements), system characteristics (e.g., scalability), and methodological rigor. The inclusion of the Methodology dimension allows us to systematically assess how problems are framed, investigated, and resolved in existing research, identifying gaps in methods (e.g., underuse of AI-driven optimization) and opportunities for methodological innovation.

2.2 Data Sources and Study Selection

This review is based on a comprehensive and systematic search of academic and industry-related literature to ensure broad coverage of relevant studies in the domains of CAD/CAM integration, AI in manufacturing, and CNC toolpath optimization. The selected sources include peer-reviewed journal articles, conference papers, and book chapters, along with a curated set of industry reports and white papers to capture practical implementations of emerging technologies.

2.2.1 Data Sources

To maintain academic rigor and reliability, the following key databases were utilized:

- Scopus – for its extensive indexing of engineering and AI-related publications.
- Web of Science – providing a broad range of peer-reviewed studies in advanced manufacturing
- Google scholar & ResearchGate – used selectively to retrieve literature, such as industry reports and white papers, ensuring coverage of real-world implementations and emerging trends.

2.2.2 Search Strategy

A structured search strategy was employed, using Boolean operators to refine results and ensure the retrieval of high-quality studies. The primary search terms used included: CAD–CAM integration, Industry 4.0, Industry 5.0, AI in manufacturing, NC code generation, feature recognition, toolpath optimization, and human-machine collaboration.

To enhance relevance, secondary qualifiers such as sustainability, interoperability, and systematic review were incorporated. The research was limited to studies published between January 2000 and March 2025, ensuring a focus on recent advancements while covering historical developments in AI-driven manufacturing. In addition to direct search results, the reference lists of selected articles were also reviewed to identify further relevant studies, helping to ensure a comprehensive literature base.

2.2.3 Inclusion and Exclusion Criteria

To maintain focus and relevance, inclusion and exclusion criteria were defined as follows:

- Inclusion Criteria:
  - Studies published between 2000 and 2025, reflecting more than two decades of advancements in CAD–CAM integration.
  - Research addressing CAD–CAM workflows, interoperability, or automation in the context of I4.0 or I5.0.
  - Studies incorporating AI, knowledge-based systems, or other innovative approaches to bridge the CAD–CAM gap.
  - Peer-reviewed articles, conference proceedings, or authoritative reviews offering empirical or theoretical insights.
- Exclusion Criteria:
  - Studies unrelated to manufacturing or CAD–CAM processes (e.g., pure software development without manufacturing applications).
  - Non-English publications or those lacking sufficient methodological detail.
  - Duplicates or redundant publications from the same research group with no significant new contributions.

2.3 Data Extraction and Analysis

Data extraction was conducted manually using a standardized Excel template aligned with the TCCM framework. In addition to capturing the four core dimensions, the template included several other descriptive and analytical fields to support a comprehensive review. Specifically, the following elements were recorded for each study:

- Bibliographic details: Paper title, authors, year of publication, keywords, journal/conference name.
- Research context: Study aim/goals, research goals.
- Analyzed dimensions:
  - Theory: Theoretical models or conceptual frameworks underlying CAD–CAM integration (e.g. systems theory, CPS).
  - Context: Industrial settings (e.g., automotive, aerospace), organizational factors, or sustainability considerations.
  - Characteristics: Technical features (e.g., AI algorithms, file formats) or organizational factors influencing interoperability.
  - Methodology: Research approaches (e.g., case studies, simulations, experiments) and their reported limitations.
  - Analytical fields: identified gaps, suggested future research directions and main findings.

This structured approach enabled both qualitative syntheses, to identify thematic trends, theoretical orientations, and methodological patterns, and basic quantitative summaries, such as publication year distribution and research domain coverage. Data management and visualization were supported using Microsoft Excel and Python, while Zotero was used for literature organization and InstaText assisted in refining the academic writing style. The detailed and traceable extraction process supports transparency and replicability of the review.

3 RESULTS OF THE SYSTEMATIC LITERATURE REVIEW

This section summarizes the results of the reviewed literature on CAD–CAM integration in the context of I4.0 and I5.0. The analysis follows standardized framework, to ensure a structured and comprehensive review. In addition to presenting the evidence, the key patterns, challenges and opportunities are discussed, considering the research objectives.

3.1 Overview of Included Studies

This SLR includes a total of 51 peer-reviewed studies published between 2002 and 2025. Although the search covered the entire period from 2000 to 2025, the earliest relevant study in this period was published in 2002. The overview shows the development of academic interest in CAD–CAM integration in the context of I4.0 and I5.0. Figure 1 shows the number of articles and conference papers published per year as well as a 3-year moving average trend line representing the overall progression of publications.

As can be seen from Fig. 1, the volume of publications remained relatively low and stable between 2002 and 2015, averaging around one to two publications per year. From 2016 onwards, a modest increase can be observed, with more consistent growth after 2018. The number of studies peaked in 2024 with a total of eight publications, indicating increased research attention and relevance of CAD–CAM integration in recent years. The 3-year moving average, marked with a black dashed line in Fig. 1, confirms this upward trend and signals continued momentum in this area.

In terms of dissemination channels, articles dominate the literature and account for most publications, while conference papers have also gained visibility in recent years, particularly from 2019 onwards. This indicates a growing interest in disseminating preliminary or applied research results via academic conferences, possibly reflecting the increasing pace of technological innovation and industry involvement.

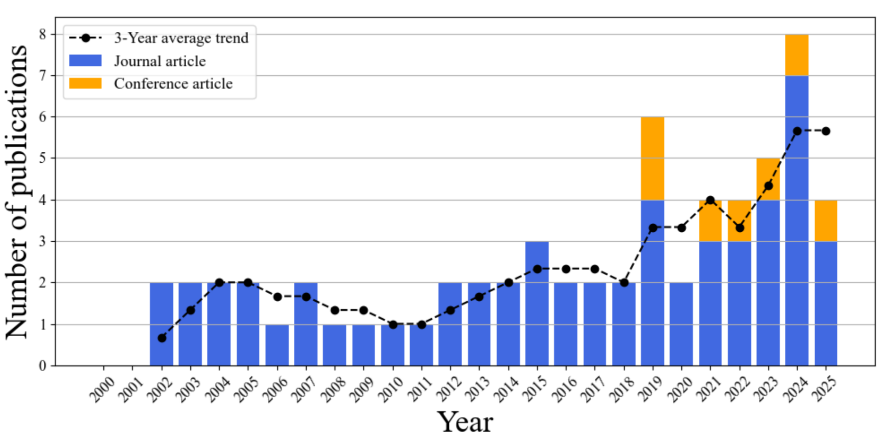

Fig. 1. Annual distribution of articles and conference contributions with a trend line

3.2 Theoretical Foundations

Integrating theoretical foundations into CAD–CAM research is crucial to guide system design, enable model-driven automation and ensure scalability across industrial applications. In the era of I4.0 and more recently I5.0, theory played a central role in aligning smart manufacturing technologies with broader technical, organizational and societal goals. To evaluate the conceptual basis of current research, each study in this review was assessed based on its stated or implied theoretical basis. Based on a thematic analysis, the identified theories were grouped into six overarching categories, which are summarized in Table 1. These categories reflect the main conceptual approaches underlying CAD–CAM integration research over the past 25 years.

Table 1. Theoretical Foundations in CAD-CAM Integration

Category	Description	Examples/Applications
ML & AI	Use of ML algorithms for prediction, classification, or optimization tasks	ANN for process modeling [38] DL for toolpath recognition [39] RL for CNC control [21] GANs for toolpath generation[40]
Optimization algorithms	Swarm-based and evolutionary algorithms applied to improve machining outcomes	NSGA-II for multi-objective optimization [41] PSO for toolpath adaptation [42] GA for machining time reduction [43] GSA for tool selection [44]
Feature/ Knowledge-Based Systems	Utilization of CAD features, KBE, and rule-based decision systems	Feature-based machining [45] Knowledge-based process planning [45] CAD/CAM integration for orthopedic/ dental workflows [46]
CPS/Digital Twins	Digital representations of physical systems for control and maintenance	Digital twins for predictive maintenance [47] Multi-agent systems [48] CPS for smart manufacturing [49]
High-Level Programming / Standards	Abstractions of low-level CNC code through semantic frameworks	STEP-NC for feature-based programming [50] Modular robotic machining [51] AM programming standards [52]
Geometric / Mathematical models	Theories improving geometric modeling and toolpath accuracy	Voxelization for complex surfaces [53] Adaptive isocurves [54] FRep for CAD/CAM correctness [55]

Taken together, these six categories reflect the various theoretical foundations that have shaped research into CAD–CAM integration. In practice, these theoretical categories often merge into hybrid approaches. For instance, ML methods such as artificial neural networks (ANNs) and generative adversarial networks (GANs) are used to enhance CPS and digital twins by predicting toolpaths. Similarly, knowledge-based engineering (KBE) frameworks integrate with high-level standards like STEP-NC (a semantic computer navigated control (CNC programming protocol) to support feature-driven toolpath generation. Optimization approaches like non-dominated sorting genetic algorithms (NSGA-II), particle swarm optimization (PSO), and gravitational search algorithms (GSA) are widely used for machining parameter tuning. Geometric modeling concepts such as function representation (FRep) and voxel-based techniques further reinforce CAD–CAM correctness and accuracy. Such synergies reinforce the impact of each theory and promote innovative CAD–CAM solutions tailored to I4.0 and I5.0 demands. These foundations also overlap with I5.0's focus on human-centeredness, sustainability and resilience. ML and AI support sustainability through predictive maintenance that reduces waste, while CPS improve resilience by enabling adaptive manufacturing systems. However, the limited presence of human-centered theories, such as cognitive ergonomics or socio-technical systems, suggests that CAD–CAM research has not yet fully embraced I5.0's focus on human–machine collaboration, indicating a potential area for theoretical expansion. These categories reflect the main conceptual approaches underlying CAD–CAM integration research over the past 25 years, and their temporal distribution is illustrated in Fig. 2.

3.3 Application Contexts

The studies examined were conducted in a variety of industrial, technical and organizational contexts, reflecting the broad applicability of CAD–CAM integration solutions. Analyzing the contextual focus of the individual studies provides insight into where and how such technologies are used and tested. Based on the content analysis, three main dimensions were identified: industry domains, enterprise types, and technological environments, each depicting unique facets of application environments. These are summarized in Table 2.

While Table 2 summarizes the three primary contextual dimensions (industry domain, enterprise type, and technological environment) it is also important to recognize several recurring challenges in CAD–CAM integration identified across the reviewed studies.

In this context, computer aided process planning (CAPP) systems play a pivotal role in bridging the gap between CAD and CAM. The reviewed studies include manual programming inefficiencies, such as time-consuming G-code authoring and limited reusability of strategies [58]; discontinuities in CAD–CAM-CNC integration, where data loss or misalignment occurs between design, planning, and execution stages [40]; and a lack of feedback and adaptivity,

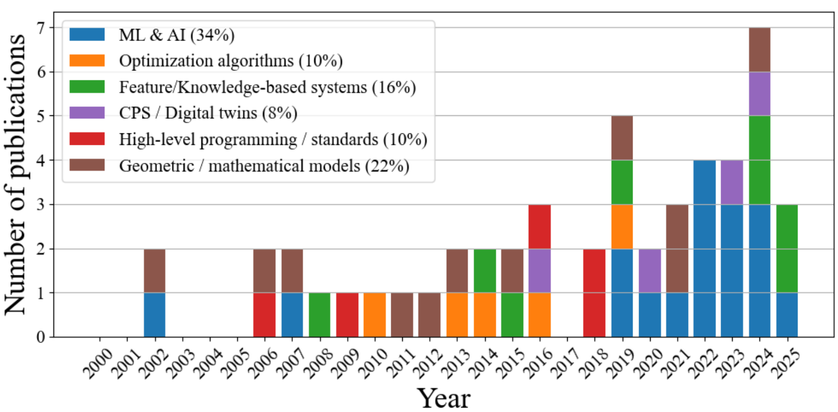

Fig. 2. Annual distribution of studies by theoretical category, with legend showing overall category share

reflected in the absence of closed-loop control or learning capabilities in conventional systems [62].

Toolpath optimization is the most prominent technical theme, appearing in over 40 % of the reviewed studies. It reflects the ongoing challenge of generating efficient and adaptable machining paths, often in connection with precision manufacturing, AI-driven planning, and CNC automation—key elements of I4.0.

Table 2. Application contexts of CAD–CAM integration by dimensions

Dimension	Category / Focus area	Description / Notes
Industry domains	Aerospace, Automotive, Tooling, Die/Mold, Medical, Dental, Orthotics, Micromachining	Common use cases include 5-axis machining, dental restoration, orthotic insole production, etc. [10,46,56]
	Precision manufacturing	Focused on toolpath accuracy, freeform surface machining, CNC optimization [54]
Enterprise type	Large enterprises/labs	Advanced CNC setups, digital twins, robotic systems, smart factories [50]
	Small & medium enterprises (SMEs)	Rapid tooling, low-batch manufacturing, focus on ease of setup and cost-effectiveness [57]
Technol-ogical environ-ments	Traditional CAM environments	Focused on automating or enhancing legacy workflows (e.g., manual G-code, static toolpaths) [58]
	Integrated CAD, CAM, CAE, CAPP systems	Studies leveraging interconnected design and manufacturing toolchains [59]
	High-level programming (e.g., STEP-NC)	Transition from G-code to semantic, feature-based CNC programming [60]
	Cloud-based/Adaptive systems	Real-time optimization, digital threads, feedback control, intelligent machining [61]

The rise of cloud-based platforms, digital twins, and adaptive control further supports I4.0 goals of connectivity, flexibility, and real-time responsiveness.

Conversely, applications in dental and orthopedic manufacturing reflect I5.0 priorities, such as personalization and human–machine collaboration. Attention to SMEs also signals a push toward accessible and scalable CAD–CAM solutions. Finally, interest in high-level programming models like STEP-NC marks a shift from rigid G-code to more semantic and interoperable approaches.

3.4 Characteristics of CAD–CAM Integration

The studies examined present a wide range of technical features and architectural implementations designed to improve CAD–CAM integration in the context of I4.0 and I5.0. This section analyzes the functional and technological features reported in the selected literature, focusing on how the integration is realized, what types of automation are implemented and what elements contribute to the adaptability, intelligence and efficiency of the system.

To structure this analysis, the features have been grouped into six overarching themes based on their core function and implementation strategy: AI and ML, toolpath optimization, feature recognition and CAD parsing, real-time systems and feedback, data models & interoperability, and hybrid/integrated architectures. Table 3 provides a summary of the distribution of studies across these thematic categories, along with a selection of representative examples and methodologies that highlight key developments within each group.

The distribution of studies reflects the field's prioritization of AI-driven automation and computational optimization to address CAD–CAM integration challenges. The dominance of AI & ML (31.4 %) and Toolpath optimization (23.5 %) highlights a strong focus on intelligent, adaptive systems capable of self-learning and real-time decision-making. For instance, optimization techniques such as self-supervised DL and evolutionary optimization are increasingly used to automate toolpath generation and process parameter tuning, reducing reliance on manual interventions.

Table 3. Distribution of representative studies across CAD–CAM integration characteristics

Characteristic theme	Description	Share of studies
AI & ML	Self-supervised DL with voxel-based RNNs [58] ANN for adaptive toolpath generation [38] Evolutionary optimization & simulation models [41] Contrastive self-supervision for feature segmentation [63]	31.4 % 16 studies
Toolpath optimization	Voxelization, and B-spline interpolation for smooth toolpaths [64] Deep graph RL for adaptive toolpath optimization [59] Evolutionary algorithms for parameter optimization [44] PSO variants for tool movement constraints [42]	23.5 % 12 studies
Hybrid/ integrated architectures	Semi-automated Matlab for trajectory analysis [56] Strategic frameworks for integrated manufacturing [60]	25.5 % 13 studies
Feature recognition & CAD parsing	STL (stereolitography)-based feature extraction & segmentation [65] DNN on structured descriptors [39]	7.8 % 4 studies
Real-Time systems & feedback	RL model for toolpath control [66] 3D vision for adaptive monitoring [61]	5.9 % 3 studies
Data models & inter-operability	FRep–based CAD/CAM with topology optimization [55] Object oriented model for NC programming [67]	5.9 % 3 studies

Meanwhile, Hybrid/integrated architectures (25.5 %) demonstrate efforts to unify design, simulation, and execution through frameworks like STEP-NC and MATLAB-based tools, reflecting I4.0's emphasis on CPS integration. However, underrepresented themes such as feature recognition & CAD parsing (7.8 %) and data models & interoperability (5.9 %) signal gaps in addressing persistent challenges like dynamic CAD data translation and system interoperability. Similarly, the limited focus on real-time systems & feedback (5.9 %) underscores the need for more empirical validation of adaptive monitoring and control mechanisms in physical machining environments.

3.5 Research Methodologies

The methodological foundations of the reviewed studies highlight the interdisciplinary approaches to CAD–CAM integration, reflecting the field's experimental and computational complexity. Five overarching methodological categories emerged from the analysis (Table 4): (1) AI and ML modeling, (2) simulations and algorithm validation, (3) STEP-NC and CPS system development, (4) experimental machining, and (5) reviews and analytical contributions. Table 4 summarizes these approaches, their key techniques, applications, and representative references.

AI and ML Modeling dominate the field, accounting for 49 % of studies (Figure 3). These works employ various DL architectures, such as ANN, CNN, RL, and generative models. Applications include intelligent toolpath generation, feature recognition, and adaptive machining, underscoring the transformative role of data-driven intelligence in automating and optimizing digital manufacturing processes. Simulations and algorithm validation represent 21.6 %

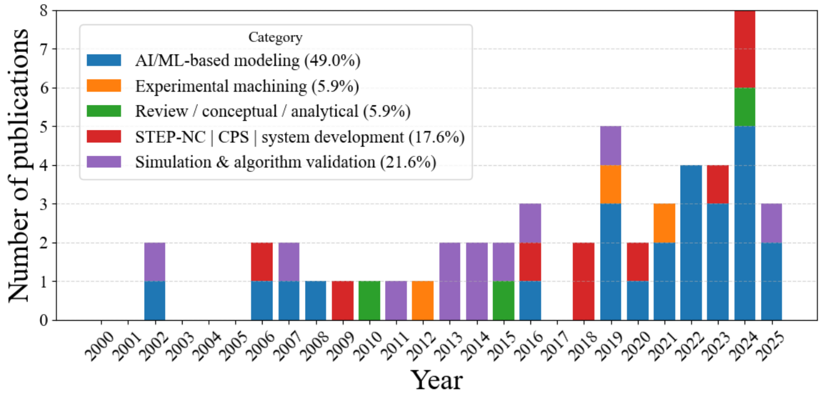

Fig. 3. Yearly distribution of studies by research methodology

of methodologies. Techniques like PSO and numerical simulations are widely used to validate toolpath strategies, cutting parameters, and process control systems in virtual environments. These approaches reduce reliance on physical prototyping by enabling pre-testing of computational models. STEP-NC, CPS, and system development (17.6 % of studies) focus on advancing interoperability in manufacturing systems. Innovations include plug-and-produce automation frameworks, machine-interpretable NC code standards, and architectures validated in industrial robotic environments. These efforts aim to bridge gaps between design and execution phases in CAD–CAM workflows. Experimental machining (5.9% of studies) emphasizes practical validation through CNC machine testing, toolpath design, and process reliability analysis. While underrepresented, these works provide critical insights into the physical realities of CAM execution, such as parameter tuning and material behavior. Reviews and analytical contributions (5.9 %) remain scarce, highlighting a gap in meta-level synthesis and theoretical frameworks. Structured reviews and interdisciplinary conceptual models are needed to unify fragmented advancements and establish robust benchmarks for future research.

Table 4. Overview of methodological approaches in CAD–CAM integration

Research approach	Key techniques/ methods	Example applications	Refs.
AI and ML modeling	DL architectures (ANN,CNN, RL), regression, generative models	Intelligent toolpath generation, feature recognition, adaptive machining	[20-22,30, 67,69,70, 73,74]
Simulations and algorithm validation	PSO, GA, GSA, numerical simulations	Validating toolpath strategies, cutting parameters, process control systems in virtual environments	[42,44,55, 68,69]
STEP-NC, CPS, system development	New system architectures, plug-and-produce frameworks, machine-interpretable NC code standards	Industrial/robotic machining environments	[47-52,70]
Experimental machining	Practical testing of CNC machines, toolpath design, process reliability	Physical realities of CAM execution, parameter tuning	[53,64,71]
Reviews, conceptual, and analytical contributions	Structured reviews, benchmarking frameworks, interdisciplinary conceptual models	Meta-level synthesis, theoretical framework development	[57]

4 DISCUSSION

This SLR synthesizes more than two decades of research on CAD–CAM integration and intelligent toolpath generation through the TCCM framework. The results reveal an evolution from the automation-focused strategies of I4.0 toward I5.0's emphasis on human-centric and sustainable manufacturing. This transition mirrors wider industrial and societal demands for inclusivity, adaptability, and environmental accountability in production systems.

AI and ML dominate the theoretical foundations, underpinning advances in feature recognition, adaptive toolpath planning, and predictive maintenance. However, theoretical models incorporating human factors, socio-technical interaction, and sustainability are scarce, limiting alignment with I5.0 principles. While CPS and digital twins offer strong potential for feedback-driven manufacturing, their industrial deployment remains limited, signaling a gap between conceptual readiness and real-world integration.

From an application standpoint, adoption is concentrated in high-precision industries, where geometric complexity and customization needs justify investment in intelligent CAD–CAM workflows. Although SMEs show growing interest, financial constraints, workforce training needs, and integration barriers hinder uptake. This calls for solutions that are scalable, cost-effective, and compatible with diverse industrial infrastructures. Cloud-based adaptive systems and STEP-NC offer viable alternatives to conventional workflows, but persistent interoperability issues slow adoption.

Technologically, AI-driven automation and optimization dominate CAD–CAM integration, with precision and efficiency as central objectives. Yet, unresolved interoperability challenges (rooted in fragmented data standards, proprietary formats, and insufficient CAD–CAM–CNC integration) limit seamless workflows. Sustainability-focused innovations, such as material efficiency and energy optimization, are increasing but remain secondary to automation goals, indicating the need to embed environmental metrics into core CAD–CAM strategies.

Methodologically, the literature is led by AI/ML-based modeling, followed by simulation-based validation and fewer experimental studies. While virtual and data-driven approaches accelerate design cycles, the lack of experimental verification, standardized datasets, and consistent reporting weakens reproducibility and comparability. Combining physical and virtual validation, and establishing shared benchmarks, would improve industrial credibility and scalability.

Key gaps persist across all TCCM dimensions: the shortage of large, validated datasets; difficulties in freeform surface recognition; limited cross-domain model generalizability; and the lack of robust solutions for real-time toolpath adaptation and force control. The slow adoption of STEP-NC, coupled with cybersecurity and interoperability constraints, particularly affects SMEs and restricts the scalability of advanced CAD–CAM solutions.

Addressing these gaps will require coordinated research and development efforts across four strategic areas:

1. Comprehensive, annotated, multimodal datasets. Datasets that integrate geometry, process parameters, sensor streams, and toolpath data are essential for developing robust AI models and achieving semantic interoperability through asset administration shells. However, most current studies depend on limited or proprietary datasets, which hampers reproducibility and scalability. Progress is constrained by the absence of standardized formats, low data variability, and intellectual property concerns. Advancing the field will require open-access repositories, harmonized CAD/CAM–sensor datasets, and the use of synthetic data generation to broaden coverage while safeguarding sensitive information.
2. Interpretable, transferable, and robust AI algorithms. Developing AI algorithms that combine interpretability, cross-domain transferability, and operational robustness is crucial for advancing CAD–CAM integration. Hybrid approaches that merge geometric reasoning methods (e.g., voxelization) with simulation-informed training and adaptive control can help bridge the gap between virtual optimization and real-world execution. However, many existing models remain opaque and narrowly specialized, which limits trust, adaptability, and scalability. Progress will depend on the adoption of explainable AI techniques, domain-adaptive learning strategies, and open-source, modular plug-and-play toolkits to facilitate seamless integration into diverse manufacturing environments.
3. Practical implementation of standards. Effective CAD–CAM integration depends on adopting and operationalizing existing yet underutilized standards such as STEP-NC and OPC UA [72]. These can be supported through middleware and integration layers that ensure compatibility across heterogeneous systems, enabling consistent data flow between design, manufacturing, and monitoring environments. Harmonizing communication protocols for Human–Machine Interfaces (HMIs) is equally critical. Advancing this area will require collaborative standard adoption, vendor-neutral integration solutions, and industry-wide alignment on interface and protocol specifications.
4. Human-centered interfaces. Human-centered interfaces should be designed to enhance operator capabilities, aligning CAD–CAM integration with I5.0's collaborative, ethical, and inclusive principles. In this context, inclusive technologies refer to solutions that are accessible across different operator skill levels, adaptable to diverse manufacturing environments (including SMEs), and interoperable with heterogeneous hardware and software systems. Human-centered interfaces will be used as guidelines, which should include:
   - Operator-focused interaction tools – Use visual dashboards, voice-enabled assistants, and intelligent HMIs to improve situational awareness, support explainable AI decisions, and allow timely manual intervention.
   - Integration of advanced LLMs – Incorporate well-known large language models such as GPT-5, LLaMA 3, Claude, and Grok-4 to enable multilingual natural language interaction, real-time troubleshooting, and automated code or G-code optimization.
   - Design engineer practices – Provide structured 3D models with standardized representations (e.g., B-rep, STEP-NC) and embedded machining metadata to ensure smooth downstream use in CAM and HMI systems.
   - Usability, transparency, and adaptability – Maintain operator engagement as active decision-makers, fostering trust and effective human – machine collaboration while ensuring scalability from small workshops to large enterprises.

5 CONCLUSIONS

Over the past two decades, CAD–CAM integration has advanced significantly within the I4.0 and I5.0 paradigms, evolving from automation-focused solutions toward more adaptive, sustainable, and collaborative manufacturing systems. The systematic mapping provided by this review clarifies the field's theoretical foundations, application contexts, technical innovations, and methodological practices, highlighting where progress has been made and where critical work remains. Key strategic directions emerging from this synthesis include:

- Bridging research–practice divides by embedding socio-technical and sustainability considerations directly into CAD–CAM solutions, ensuring they are deployable in diverse industrial contexts.
- Expanding accessibility through scalable, cost-effective integration strategies that address SME-specific constraints without sacrificing interoperability or performance.
- Embedding sustainability as a core metric alongside productivity and precision, ensuring material efficiency, energy optimization, and lifecycle awareness in CAD–CAM workflows.
- Leveraging advanced AI and standards (interpretable models, STEP-NC, and OPC UA) to enable adaptive, interoperable, and future-proof manufacturing ecosystems.

While this review focuses on peer-reviewed literature, future studies should combine industrial case evidence with academic research to capture region-specific practices, operational constraints, and emerging innovations. Addressing these priorities will accelerate the transition toward manufacturing systems that are not only technologically advanced, but also inclusive, resilient, and environmentally responsible—fully embodying the collaborative ethos of I5.0.

References

[1] Horvat, D., Kroll, H., Jäger, A. Researching the effects of automation and digitalization on manufacturing companies' productivity in the early stage of Industry 4.0. *Procedia Manuf* 39 886-893 (2019) **DOI:10.1016/j.promfg.2020.01.401**.

[2] Ojstersek, R., Buchmeister, B., Vujica Herzog, N. Use of data-driven simulation modeling and visual computing methods for workplace evaluation. *Appl Sci* 10 7037 (2020) **DOI:10.3390/app10207037**.

[3] Kovič, K., Ojsteršek, R., Palčič, I. Simultaneous use of digital technologies and industrial robots in manufacturing firms. *Appl Sci* 13 5890 (2023) **DOI:10.3390/app13105890**.

[4] Pozzi, R., Rossi, T., Secchi, R. Industry 4.0 technologies: critical success factors for implementation and improvements in manufacturing companies. *Prod Plan Control* 34 139-158 (2023) **DOI:10.1080/09537287.2021.1891481**.

[5] Aheleroff, S., Huang, H., Xu, X., Zhong, R.Y. Toward sustainability and resilience with Industry 4.0 and Industry 5.0. *Front Manuf Technol* 2 951643 (2022) **DOI:10.3389/fmtec.2022.951643**.

[6] Regassa Hunde, B., Debebe Woldeyohannes, A. Future prospects of computer-aided design (CAD) - a review from the perspective of artificial intelligence (AI), extended reality, and 3D printing. *Results Eng* 14 100478 (2022) **DOI:10.1016/j.rineng.2022.100478**.

[7] Feldhausen, T., Heinrich, L., Saleeby, K., Burl, A., Post, B., MacDonald, E., Saldana, C., Love, L. Review of computer-aided manufacturing (CAM) strategies for hybrid directed energy deposition. *Addit Manuf* 56 102900 (2022) **DOI:10.1016/j.addma.2022.102900**.

[8] Xu, X., Wang, L., Newman, S.T. Computer-aided process planning - a critical review of recent developments and future trends. *Int J Comput Integr Manuf* 24 1-31 (2011) **DOI:10.1080/0951192X.2010.518632**.

[9] Toquica, J.S., Zivanovic, S., Bonnard, R., Rodriguez, E., Alvares, A.J., Ferreira, J.C.E. STEP-NC-based machining architecture applied to industrial robots. *J Braz Soc Mech Sci Eng* 41 314 (2019) **DOI:10.1007/s40430-019-1811-y**.

[10] Lasemi, A., Xue, D., Gu, P. Recent development in CNC machining of freeform surfaces: a state-of-the-art review. *Comput Aided Des* 42 641-654 (2010) **DOI:10.1016/j.cad.2010.04.002**.

[11] Fu, Y., Zhu, G., Zhu, M., Xuan, F. Digital twin for integration of design-manufacturing-maintenance: an overview. *Chin J Mech Eng* 35 80 (2022) **DOI:10.1186/s10033-022-00760-x**.

[12] Han, J., Kang, M., Choi, H. STEP-based feature recognition for manufacturing cost optimization. *Comput Aided Des* 33 671-686 (2001) **DOI:10.1016/S0010-4485(01)00071-9**.

[13] Wu, D., Rosen, D.W., Schaefer, D. Cloud-based design and manufacturing: status and promise. Schaefer, D. (ed.) *Cloud-Based Design and Manufacturing (CBDM)* 1-24 (2014) **DOI:10.1007/978-3-319-07398-9_1**.

[14] Pratt, M.J. Introduction to ISO 10303-the STEP standard for product data exchange. *J Comput Inf Sci Eng* 1 102-103 (2001) **DOI:10.1115/1.1354995**.

[15] Han, J., Pratt, M., Regli, W.C. Manufacturing feature recognition from solid models: a status report. *IEEE Trans Robot Autom* 16 782-796 (2000) **DOI:10.1109/70.897789**.

[16] Xu, X., Hinduja, S. Recognition of rough machining features in 212D components. *Comput Aided Des* 30 503-516 (1998) **DOI:10.1016/S0010-4485(97)00090-0**.

[17] Wu, Z., Liang, C. A review and prospects of manufacturing process knowledge acquisition, representation, and application. *Machines* 12 416 (2024) **DOI:10.3390/machines12060416**.

[18] Al-wswasi, M., Ivanov, A., Makatsoris, H. A survey on smart automated computer-aided process planning (ACAPP) techniques. *Int J Adv Manuf Technol* 97 809-832 (2018) **DOI:10.1007/s00170-018-1966-1**.

[19] Leo Kumar, S.P. State of the art-intense review on artificial intelligence systems application in process planning and manufacturing. *Eng Appl Artif Intell* 65 294-329 (2017) **DOI:10.1016/j.engappai.2017.08.005**.

[20] Zhang, Z., Jaiswal, P., Rai, R. FeatureNet: machining feature recognition based on 3D convolution neural network. *Comput Aided Des* 101 12-22 (2018) **DOI:10.1016/j.cad.2018.03.006**.

[21] Juraev, M., Abrorov, A., Akhmedova, K., Abdullayev, S. Optimization of CNC machining tool paths using reinforcement learning techniques. *Appl Mech Mater* 923 39-48 (2024) **DOI:10.4028/p-4pj98Q**.

[22] Li, C., Zheng, P., Yin, Y., Wang, B., Wang, L. Deep reinforcement learning in smart manufacturing: a review and prospects. *CIRP J Manuf Sci Technol* 40 75-101 (2023) **DOI:10.1016/j.cirpj.2022.11.003**.

[23] Wang, J., Ma, Y., Zhang, L., Gao, R.X., Wu, D. Deep learning for smart manufacturing: methods and applications. *J Manuf Syst* 48 144-156 (2018) **DOI:10.1016/j.jmsy.2018.01.003**.

[24] Bécue, A., Praça, I., Gama, J. Artificial intelligence, cyber-threats and Industry 4.0: challenges and opportunities. *Artif Intell Rev* 54 3849-3886 (2021) **DOI:10.1007/s10462-020-09942-2**.

[25] Kusiak, A. Smart manufacturing. *Int J Prod Res* 56 508-517 (2018) **DOI:10.1080/00207543.2017.1351644**.

[26] Doris, A.C., Alam, M.F., Nobari, A.H., Ahmed, F. CAD-Coder: an open-source vision-language model for computer-aided design code generation. *arXiv* (2025) **DOI:10.48550/arXiv.2505.14646**.

[27] Tzotzis, A., Manavis, A., Efkolidis, N., Kyratsis, P. CAD-based automated G-code generation for drilling operations. *Int J Mechatron Manuf Syst* 13 177-184 (2021) **DOI:10.54684/ijmmt.2021.13.3.177**.

[28] Yarava, V.S. AutoCAD to G-code converter. *IEEE Pune Section International Conference* 1-5 (2021) **DOI:10.1109/PuneCon52575.2021.9686541**.

[29] Nahavandi, S. Industry 5.0-a human-centric solution. *Sustainability* 11 4371 (2019) **DOI:10.3390/su11164371**.

[30] Jamwal, A., Agrawal, R., Sharma, M., Giallanza, A. Industry 4.0 technologies for manufacturing sustainability: a systematic review and future research directions. *Appl Sci* 11 5725 (2021) **DOI:10.3390/app11125725**.

[31] Culot, G., Nassimbeni, G., Orzes, G., Sartor, M. Behind the definition of Industry 4.0: analysis and open questions. *Int J Prod Econ* 226 107617 (2020) **DOI:10.1016/j.ijpe.2020.107617**.

[32] Ding, S., Feng, Q., Sun, Z., Ma, F. MBD-based 3D CAD model automatic feature recognition and similarity evaluation. *IEEE Access* 9 150403-150425 (2021) **DOI:10.1109/ACCESS.2021.3126333**.

[33] Lu, F., Zhou, G., Zhang, C., Liu, Y., Chang, F., Lu, Q., Xiao, Z. Energy-efficient tool path generation and expansion optimisation for five-axis flank milling with meta-reinforcement learning. *J Intell Manuf* (2024) **DOI:10.1007/s10845-024-02412-4**.

[34] Paul, J., Khatri, P., Kaur Duggal, H. Frameworks for developing impactful systematic literature reviews and theory building: what, why and how? *J Decis Syst* 33 537-550 (2024) **DOI:10.1080/12460125.2023.2197700**.

[35] Paul, J., Criado, A.R. The art of writing literature review: what do we know and what do we need to know? *Int Bus Rev* 29 101717 (2020) **DOI:10.1016/j.ibusrev.2020.101717**.

[36] Paul, J., Lim, W.M., O'Cass, A., Hao, A.W., Bresciani, S. Scientific procedures and rationales for systematic literature reviews (SPAR-4-SLR). *Int J Consum Stud* 45 (2021) **DOI:10.1111/ijcs.12695**.

[37] Pati, D., Lorusso, L.N. How to write a systematic review of the literature. *Health Environ Res Des J* 11 15-30 (2018) **DOI:10.1177/1937586717747384**.

[38] Balic, J., Korosec, M. Intelligent tool path generation for milling of free surfaces using neural networks. *Int J Mach Tools Manuf* 42 1171-1179 (2002) **DOI:10.1016/S0890-6955(02)00045-7**.

[39] Yeo, C., Kim, B.C., Cheon, S., Lee, J., Mun, D. Machining feature recognition based on deep neural networks to support tight integration with 3D CAD systems. *Sci Rep* 11 22147 (2021) **DOI:10.1038/s41598-021-01313-3**.

[40] Kaiser, B., Csiszar, A., Verl, A. Generative models for direct generation of CNC toolpaths. *25th International Conference on Mechatronics and Machine Vision in Practice* 1-6 (2018) **DOI:10.1109/M2VIP.2018.8600856**.

[41] Klancnik, S., Brezocnik, M., Balic, J. Intelligent CAD/CAM system for programming of CNC machine tools. *Int J Simul Model* 15 109-120 (2016) **DOI:10.2507/IJSIMM15(1)9.330**.

[42] Hsieh, H.-T., Chu, C.-H. Improving optimization of tool path planning in 5-axis flank milling using advanced PSO algorithms. *Robot Comput Integr Manuf* 29 3-11 (2013) **DOI:10.1016/j.rcim.2012.04.007**.

[43] Dodok, T., Čuboňová, N. Optimization and efficiency of toolpath generation in CAD/CAM system. *MATEC Web Conf* 299 03001 (2019) **DOI:10.1051/matecconf/201929903001**.

[44] Hrelja, M., Klancnik, S., Balic, J., Brezocnik, M. Modelling of a turning process using the gravitational search algorithm. *Int J Simul Model* 13 30-41 (2014) **DOI:10.2507/IJSIMM13(1)3.248**.

[45] Leo Kumar, S.P., Jerald, J., Kumanan, S. Feature-based modelling and process parameters selection in a CAPP system for prismatic micro parts. *Int J Comput Integr Manuf* 1-17 (2014) **DOI:10.1080/0951192X.2014.953586**.

[46] Obrovac, K., Staroveški, T., Vuković-Obrovac, J., Klaić, M. System for automated production of custom made shoe insoles. *Stroj Cas J Mech Eng* 74 81-88 (2024) **DOI:10.2478/scjme-2024-0035**.

[47] Kubota, T., Hamzeh, R., Xu, X. STEP-NC enabled machine tool digital twin. *Procedia CIRP* 93 1460-1465 (2020) **DOI:10.1016/j.procir.2020.06.004**.

[48] Nilsson, A., Danielsson, F., Svensson, B. From CAD to plug & produce: a generic structure for the integration of standard industrial robots into agents. *Int J Adv Manuf Technol* 128 5249-5260 (2023) **DOI:10.1007/s00170-023-12280-6**.

[49] Monostori, L., Kádár, B., Bauernhansl, T., Kondoh, S., Kumara, S., Reinhart, G., Sauer, O., Schuh, G., Sihn, W., Ueda, K. Cyber-physical systems in manufacturing. *CIRP Ann* 65 621-641 (2016) **DOI:10.1016/j.cirp.2016.06.005**.

[50] Suh, S.-H., Chung, D.-H., Lee, B.-E., Shin, S., Choi, I., Kim, K.-M. STEP-compliant CNC system for turning: data model, architecture, and implementation. *Comput Aided Des* 38 677-688 (2006) **DOI:10.1016/j.cad.2006.02.006**.

[51] Toquica, J.S., Živanović, S., Alvares, A.J., Bonnard, R. A STEP-NC compliant robotic machining platform for advanced manufacturing. *Int J Adv Manuf Technol* 95 3839-3854 (2018) **DOI:10.1007/s00170-017-1466-8**.

[52] Bonnard, R., Hascoët, J.-Y., Mognol, P., Stroud, I. STEP-NC digital thread for additive manufacturing: data model, implementation and validation. *Int J Comput Integr Manuf* 31 1141-1160 (2018) **DOI:10.1080/0951192X.2018.1509130**.

[53] Kukreja, A., Dhanda, M., Pande, S. Efficient toolpath planning for voxel-based CNC rough machining. *Comput Aided Des Appl* 18 285-296 (2020) **DOI:10.14733/cadaps.2021.285-296**.

[54] Ding, S., Mannan, M.A., Poo, A.N., Yang, D.C.H., Han, Z. Adaptive iso-planar tool path generation for machining of free-form surfaces. *Comput Aided Des* 35 141-153 (2003) **DOI:10.1016/S0010-4485(02)00048-9**.

[55] Popov, D., Kuzminova, Y., Maltsev, E., Evlashin, S., Safonov, A., Akhatov, I., Pasko, A. CAD/CAM system for additive manufacturing with a robust and efficient topology optimization algorithm based on the function representation. *Appl Sci* 11 7409 (2021) **DOI:10.3390/app11167409**.

[56] Maltauro, M., Vargiu, E., Tozzi, F., Ciocca, L., Meneghello, R. A semi-automated tool for digital and mechanical articulators comparative analysis of condylar path elements. *Comput Biol Med* 186 109724 (2025) **DOI:10.1016/j.compbiomed.2025.109724**.

[57] Matta, A.K., Raju, D.R., Suman, K.N.S. The integration of CAD/CAM and rapid prototyping in product development: a review. *Mater Today Proc* 2 3438-3445 (2015) **DOI:10.1016/j.matpr.2015.07.319**.

[58] Yavartanoo, M., Hong, S., Neshatavar, R., Lee, K.M. CNC-Net: self-supervised learning for CNC machining operations. *arXiv* (2023) **DOI:10.48550/arXiv.2312.09925**.

[59] Ye, L. Design and manufacturing of mechanical parts based on CAD and CAM technology. *Eng Res Express* 6 045411 (2024) **DOI:10.1088/2631-8695/ad8056**.

[60] Cha, J.-M., Suh, S.-H., Hascoet, J.-Y., Stroud, I. A roadmap for implementing new manufacturing technology based on STEP-NC. *J Intell Manuf* 27 959-973 (2016) **DOI:10.1007/s10845-014-0927-2**.

[61] Pivkin, P., Nazarenko, E., Grechishnikov, V., Kuznetsov, V., Uvarova, L., Ershov, A., Yazev, A., Nadykto, A. Digital cyber-physical system for designing and manufacturing of conical end mill. *E3S Web Conf* 592 05024 (2024) **DOI:10.1051/e3sconf/202459205024**.

[62] Zavalnyi, O., Zhao, G., Liu, Y., Xiao, W. Optimization of the STEP-NC compliant online toolpath generation for T-spline surfaces using convolutional neural network and random forest classifier. *IOP Conf Ser Mater Sci Eng* 658 012015 (2019) **DOI:10.1088/1757-899X/658/1/012015**.

[63] Wang, J., Zhu, H., Guo, H., Mamun, A.A., Xiang, C., Lee, T.H. Few-shot point cloud semantic segmentation via contrastive self-supervision and multi-resolution attention. *2023 IEEE International Conference on Robotics and Automation (ICRA)* 2811-2817 (2023) **DOI:10.1109/ICRA48891.2023.10160429**.

[64] Obrovac, K., Raos, P., Staroveški, T., Brezak, D. A method for generating toolpaths in the manufacturing of orthosis molds with a five-axis computer numerical control machine. *Machines* 12 740 (2024) **DOI:10.3390/machines12100740**.

[65] Balič, J., Klančnik, S., Brezovnik, S. Feature extraction from CAD model for milling strategy prediction. *Stroj Vestn-J Mech E* 301-307 (2008).

[66] Zhang, Y., Li, Y., Xu, K. Reinforcement learning-based tool orientation optimization for five-axis machining. *Int J Adv Manuf Technol* 119 7311-7326 (2022) **DOI:10.1007/s00170-022-08668-5**.

[67] Rauch, M., Laguionie, R., Hascoet, J.-Y., Xu, X. Enhancing CNC manufacturing interoperability with STEP-NC. *J Mach Eng* 9 26-37 (2009).

[68] Mladenovic, G., Tanovic, L., Ehmann, K. Tool path generation for milling of free form surfaces with feed rate scheduling. *FME Trans* 43 9-15 (2015) **DOI:10.5937/fmet1501009m**.

[69] Dhanda, M., Pande, S. Adaptive tool path planning strategy for freeform surface machining using point cloud. *Comput Aided Des Appl* 16 289-307 (2018) **DOI:10.14733/cadaps.2019.289-307**.

[70] Liao, J., Huang, Z. Data model-based toolpath generation techniques for CNC milling machines. *Front Mech Eng* 10 1358061 (2024) **DOI:10.3389/fmech.2024.1358061**.

[71] Giannakis, A., Vosniakos, G.C. Parametric multi-axis tool path planning for CNC machining: the case of spur gears. *Int J Manuf Res* 7 354 (2012) **DOI:10.1504/IJMR.2012.050101**.

[72] Ji, T., Xu, X. Exploring the integration of cloud manufacturing and cyber-physical systems in the era of Industry 4.0 - an OPC UA approach. *Robot Comput Integr Manuf* 93 102927 (2025) **DOI:10.1016/j.rcim.2024.102927**.

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Inteligentno generiranje poti orodja: sistematični pregled integracije CAD–CAM v Industriji 4.0 in 5.0

Povzetek *Pregled literature raziskuje napredek na področju integracije računalniško podprtega konstruiranja in računalniško podprte proizvodnje (CAD–CAM) ter generiranja poti orodja, pri čemer analizira razvoj v okviru Industrije 4.0 in Industrije 5.0 (I5.0). S pomočjo pristopa po teoriji–kontekstu–značilnostih–metodologiji (TCCM) študija sintetizira 51 recenziranih raziskav (v obdobju 2000–2025) ter analizira teoretične osnove, industrijske aplikacije, tehnične inovacije in metodološke trende. Ugotovitve razkrivajo, da raziskave močno zaznamujejo umetna inteligenca (UI) in strojno učenje, ki poganjata preboje na področju prepoznavanja značilnosti, adaptivne optimizacije poti orodja in napovednega vzdrževanja. Vendar pa človeško-usmerjene rešitve, ki so osrednjega pomena za I5.0, kot je sociotehnično sodelovanje, ostajajo premalo raziskana. Panoge z visoko natančnostjo (letalska in vesoljska, biomedicinska) vodijo pri uvajanju, medtem ko mala in srednja podjetja (MSP) zaostajajo zaradi omejenih virov. S tehnološkega vidika obetajo avtomatizacija, ki temelji na UI in standardi STEP-NC, a vrzeli v interoperabilnosti ostajajo zaradi razdrobljenih podatkovnih modelov in zastarelih sistemov. Metodološko prevladuje modeliranje na osnovi UI (49 % raziskav), eksperimentalna validacija in sociotehnična ogrodja pa ostajata redka. Ključne vrzeli, ki so bile zaznane v študiji, vključujejo omejeno sprotno prilagodljivost, pomanjkanje zadostnih učnih podatkovnih zbirk za učenje modelov UI, ter počasno uvajanje trajnostnih praks. Pregled poudarja nujnost standardiziranih protokolov za izmenjavo podatkov, razširljivih rešitev za malo serijsko proizvodnjo ter razvoj modelov sodelovanja med človekom in UI, ki bi CAD–CAM integracijo uskladili s trajnostnimi in odpornimi cilji I5.0. Z odpravljanjem teh vrzeli prispeva pregled k oblikovanju načrta za napredno, inteligentno in človeku usmerjeno proizvodno okolje.*

Ključne besede *CAD–CAM integracija, Industrija 4.0, Industrija 5.0, optimizacija poti orodja, umetna inteligenca (UI), teorija–kontekst–značilnosti–metodologija (TCCM)*