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Review Article

Sustainable Manufacturing in the Digital Era: A Comprehensive Review of Enabling Technologies, Life Cycle Engineering, and Educational Imperatives

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A R T I C L E I N F O

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A B S T R A C T

The convergence of digital technologies, sustainable materials, and advanced manufacturing processes represents a paradigm shift in industrial production. This comprehensive review examines the interconnected pillars of sustainable manufacturing, focusing on four critical domains: additive manufacturing and life cycle engineering, engineering graphics literacy as a foundation for manufacturing communication, biodegradable polymers as materials for environmentally responsible production, and quality assurance through machine learning-enabled defect detection. Through a structured literature review and comparative synthesis of peer-reviewed studies published between 2014 and 2026, this paper investigates how deficiencies in technical drawing competency among engineering graduates contribute to manufacturing waste and rework while simultaneously examining how advances in additive manufacturing, life cycle engineering, biodegradable polymers, and machine learning-enabled quality assurance can collectively support sustainable manufacturing and circular economy objectives. The review reveals that engineering graphics competency gaps are associated with significant manufacturing inefficiencies, with industry professionals reporting production delays (79.55%), rework costs (78.41%), and scrap generation (73.86%) attributable to drawing-related errors. Concurrently, advances in additive manufacturing demonstrate potential for reducing material waste by 40-60% through topology optimization and part consolidation, though these benefits are highly context-dependent and require comprehensive life cycle assessment. Biodegradable polymers processed through additive manufacturing platforms offer pathways to circular manufacturing, with materials such as PLA, PCL, and PBAT showing compatibility with fused deposition modeling, direct ink writing, and digital light processing. The paper proposes an integrated framework connecting engineering education reform, sustainable material development, and advanced manufacturing technologies to achieve operational excellence and environmental responsibility. Key findings indicate that bridging the education-industry gap in technical drawing competency could substantially reduce manufacturing waste, while strategic adoption of life cycle engineering principles in additive manufacturing could decrease environmental impacts by 20-40% in transportation sectors. The study concludes that sustainable manufacturing requires simultaneous advancement in human capital development, material innovation, process technology, and quality assurance systems, supported by standardized curricula, industry-academia partnerships, and comprehensive life cycle assessment frameworks.

1. Introduction

The imperative for sustainable manufacturing has never been more pressing. Global manufacturing accounts for approximately 30% of greenhouse gas emissions, consumes 54% of the world's energy resources, and generates substantial waste streams that burden ecosystems and communities (Geyer et al., 2017; Rosenboom et al., 2022). In response, industries worldwide are pursuing strategies to reduce environmental impact while maintaining economic competitiveness and operational efficiency. This dual challenge—achieving sustainability without sacrificing productivity—requires fundamental changes in how products are designed, materials are selected, manufacturing processes are executed, and quality is assured.

The fourth industrial revolution, commonly termed Industry 4.0, represents the paradigmatic convergence of the physical industrial domain with innovative digital technologies (Kagermann et al., 2013; Lasi et al., 2014). Initially conceptualized in Germany to sustain global competitiveness and address demands for mass customization, Industry 4.0 has since become a global movement reshaping industrial operations across sectors and geographies (Becker et al., 2017). The fundamental premise of Industry 4.0 lies in the integration of cyber-physical systems that monitor physical processes, create virtual counterparts of the physical world, and facilitate decentralized decision-making (Kagermann et al., 2013).

Three interconnected domains have emerged as critical enablers of sustainable manufacturing: additive manufacturing technologies with integrated life cycle engineering, engineering graphics literacy, and biodegradable polymers. Additive manufacturing (AM), commonly referred to as three-dimensional (3D) printing, has developed into a transformative and resource-efficient manufacturing approach. Unlike conventional manufacturing techniques such as injection molding, extrusion, or CNC machining, which often require energy-intensive tooling and generate considerable material waste, AM enables tool-free, layer-by-layer fabrication of complex geometries with minimal material loss (Ford & Despeisse, 2016; Peng et al., 2018). When integrated with life cycle engineering principles and biodegradable polymers, AM provides a synergistic platform for fabricating products that combine functional performance with environmental responsibility.

Engineering graphics and technical drawing represent the primary formal communication medium of manufacturing systems, conveying dimensional specifications, tolerances, surface conditions, and geometric intent across the full production chain (Sarikaya et al., 2026). When engineers misinterpret drawings, the consequences cascade through manufacturing chains in the form of scrap, rework, material waste, and energy inefficiency—outcomes that directly contradict sustainability objectives. Despite the centrality of technical drawing to industrial communication, persistent deficiencies in graduate CAD literacy and standards compliance continue to undermine manufacturing performance.

Biodegradable polymers such as polylactic acid (PLA), polycaprolactone (PCL), polybutylene succinate (PBS), and poly(butylene adipate-co-terephthalate) (PBAT) provide alternatives to conventional petroleum-derived plastics, with the capacity to degrade under controlled conditions and align with circular economy principles (Lim et al., 2026). When integrated with additive manufacturing technologies, these materials enable eco-designed products optimized not only for mechanical and functional performance but also for environmentally responsible end-of-life outcomes.

Quality assurance in manufacturing has been transformed by machine learning-enabled surface defect detection systems. Traditional manual visual inspection processes are time-consuming, inconsistent, and difficult to scale (Spackman & Butler, 2026). Advanced machine learning algorithms, including deep learning architectures and classical feature engineering approaches, offer the potential for automated, consistent, and efficient defect detection, reducing waste and improving product quality.

Despite substantial research in each of these domains individually, there remains a significant gap in understanding how they interconnect and reinforce one another within the broader context of sustainable manufacturing. This paper addresses this gap by examining the relationships between engineering graphics education, additive manufacturing with life cycle engineering, biodegradable polymer development, and machine learning-enabled quality assurance. The objectives of this paper are fourfold: first, to document the current state of engineering graphics competency among engineering graduates and its perceived consequences for manufacturing performance; second, to review recent advances in additive manufacturing and life cycle engineering; third, to examine biodegradable polymer development and compatibility with additive manufacturing platforms; and fourth, to explore machine learning applications in surface defect detection for manufacturing quality assurance.

1.1 Research Contributions

This review makes several important contributions to the sustainable manufacturing literature. First, it integrates four complementary research domains—engineering graphics education, additive manufacturing with life cycle engineering, biodegradable polymers, and machine learning-enabled quality assurance—within a single comprehensive framework, providing a holistic perspective on sustainable manufacturing. Second, the review synthesizes recent advances reported between 2014 and 2026, identifying key technological developments, implementation challenges, and emerging research trends across these interconnected domains. Third, the study proposes an integrated sustainable manufacturing framework that highlights the interdependencies between human capital development, material innovation, process technology, and intelligent quality assurance systems. Finally, the review provides practical recommendations for engineering educators, manufacturing practitioners, researchers, and policymakers to support the development of environmentally responsible, technologically advanced, and operationally efficient manufacturing systems.

2. Literature Review

2.1 Engineering Graphics and Technical Drawing Education

Technical drawing, the visual language of engineering, has roots extending to the Renaissance, when pioneers such as Leonardo da Vinci and Gaspar Monge established the foundations of orthographic projection and dimensional clarity (Sampaio, 2018). Throughout the pre-industrial and industrial eras, hand drawing formed the core of technical instruction, developing spatial awareness, scaling abilities, and proportionality using T-squares, compasses, and set squares (Sarikaya et al., 2026). This tactile experience was instrumental in building the cognitive processes associated with spatial visualization, which remains a key predictor of success in engineering-related fields (Tumkor & de Vries, 2015; Ogunkola & Knight, 2018).

The digital revolution introduced computer-aided design (CAD), augmented reality (AR), virtual reality (VR), and artificial intelligence (AI), enabling more interactive and efficient learning environments (Hiroi & Ito, 2023; Henstrom et al., 2024). Despite these innovations, educational outcomes frequently fail to meet industrial expectations. Employers consistently report that graduates lack critical competencies in interpreting complex drawings, understanding dimensional tolerances, and applying international standards such as ISO and GD&T (McLaren, 2008; Motyl et al., 2025). These deficiencies have been associated with increased scrap rates, resource waste, and production inefficiencies that undermine sustainability goals in manufacturing.

Research by Ogunkola and Knight (2018) found that technical drawing instruction significantly increases students' mental rotation ability, a key component of spatial visualization. However, the integration of CAD into curricula has introduced pedagogical tensions: as students become reliant on CAD interfaces, concerns emerge about the erosion of fundamental spatial reasoning and manual drafting skills (Ogunkola & Knight, 2018; Halim et al., 2012). Recent scholarship emphasizes hybrid pedagogical approaches that maintain the strengths of traditional methods while embracing digital affordances (Rochman, 2024; Sola-Guirado et al., 2022), including project-based learning, flipped classrooms, and AI-powered feedback mechanisms (Diez-Ibarbia et al., 2023; Fastabend et al., 2024).

The imperative for inclusive education has grown, with evidence underscoring the need for multimodal resources, accessible digital platforms, and culturally responsive content to serve diverse learner populations (Del Cerro Velázquez & Lozano Rivas, 2020; Rose & Dalton, 2009). Universal Design for Learning (UDL) offers a robust framework, advocating for information delivery in multiple modalities, including interactive animations, voice-over tutorials, 3D-printed tactile models, and screen-reader-compatible CAD platforms (Castaneda et al., 2025; Schreffler et al., 2019).

The education-industry gap in technical drawing has been well documented. Students proficient in CAD may be unfamiliar with industry standards; graduates who excel in visualization may struggle with production-ready documentation (Garland et al., 2017; Mohamed, 2024). In high-stakes sectors such as aerospace, automotive, and medical device manufacturing, even minor deviations in dimensions or geometric interpretation lead to costly errors, rework, safety risks, and material waste (Ali et al., 2024). Industry stakeholders advocate for curricular partnerships where companies develop modules, provide authentic datasets, and offer internships (Valiente Bermejo et al., 2021; Chen et al., 2020). However, the implementation of such partnerships remains limited, and empirical evidence documenting the consequences of the education-industry gap is scarce.

2.2 Additive Manufacturing and Life Cycle Engineering

Additive manufacturing has emerged as a transformative technology with significant potential for sustainable manufacturing. AM constructs parts through layer-by-layer material deposition, significantly reducing material waste compared to subtractive manufacturing (Ford & Despeisse, 2016; Peng et al., 2018). The elimination of dedicated molds and tooling lowers energy demand, shortens setup times, and enhances production flexibility. Furthermore, AM facilitates decentralized, on-demand manufacturing, enabling localized production that reduces transportation-related emissions and minimizes excess inventory (Sauerwein et al., 2019).

Life cycle engineering (LCE) is defined as "engineering activities which include the application of technological and scientific principles to manufacturing products with the goal of protecting the environment, conserving resources, encouraging economic progress, keeping in mind social concerns, and the need for sustainability, while optimizing the product life cycle and minimizing pollution and waste" (Favi et al., 2025). LCE encompasses both life cycle assessment (LCA) for environmental impacts and life cycle costing (LCC) for economic evaluation.

The integration of LCE with AM presents both opportunities and challenges. From an engineering perspective, AM technologies introduce several advantages enabling the creation of lightweight, multi-functional, and performance-optimized components (Favi et al., 2025). However, challenges related to high energy consumption, material preparation, and variability in life cycle impacts need to be addressed with dedicated life cycle analysis to ensure environmental and economic sustainability. As Favi et al. (2025) note, "Existing methods for integrating ecodesign into life cycle assessment are fragmented, with limited frameworks combining environmental and economic aspects."

Key technological parameters affecting the life cycle performance of AM include:

Material Preparation: The production of feedstock materials for AM—such as metal powders via gas atomization or polymer filaments—is energy-intensive and environmentally costly. For instance, the manufacture of 1 kg of metal powder requires 5.5 kg of argon gas, contributing significantly to air emissions (Favi et al., 2025). The embodied energy for producing metal powders ranges from 100-400 MJ/kg, compared to 20-50 MJ/kg for bulk metals.

Energy Consumption: AM processes, particularly those using lasers or electron beams (e.g., selective laser melting, direct energy deposition), are significantly more energy-intensive than conventional methods. Energy consumption for manufacturing 1 kg of product using metal AM ranges from 200-800 MJ/kg, compared to 50-200 MJ/kg for conventional machining (Favi et al., 2025).

Post-Processing: Post-processing operations such as heat treatment, machining for dimensional accuracy, and surface finishing increase the cumulative environmental burden and contribute significantly to both costs and energy use. These steps can negate many of the perceived environmental benefits of AM, particularly when the full life cycle is considered.

Design for Additive Manufacturing (DfAM) guidelines are essential to fully harness the economic, environmental, and technical advantages of AM. These guidelines help designers create parts that are resource-efficient, environmentally friendly, and meet quality requirements. Key DfAM strategies include topology optimization and generative design, part consolidation, infill pattern and density optimization, and build orientation optimization (Favi et al., 2025).

2.3 Biodegradable Polymers for Sustainable Additive Manufacturing

Biodegradable polymers are increasingly recognized as key enablers of sustainable additive manufacturing, offering a unique combination of environmental degradability, tunable mechanical performance, and compatibility across diverse printing platforms (Lim et al., 2026). Polymers such as PLA, PCL, PBS, and PBAT offer several advantages: many are partially or fully derived from renewable feedstocks, and they undergo enzymatic or hydrolytic degradation into non-toxic byproducts. Their end-of-life pathways may include industrial composting, controlled biodegradation, or chemical recycling.

The chemical architecture of biodegradable polymers plays a central role in determining their degradation behavior, physicochemical properties, and compatibility with AM processes (Lim et al., 2026). PLA is a thermoplastic aliphatic polyester synthesized from renewable biomass-derived feedstocks such as corn starch or sugarcane. Its backbone consists of hydrolytically labile ester linkages, making it susceptible to bulk hydrolysis under elevated temperature conditions (Farah et al., 2016). PCL is typically produced from fossil-derived ε-caprolactone via ring-opening polymerization, with a flexible aliphatic backbone contributing to slow degradation kinetics and excellent low-temperature processability (Woodruff & Hutmacher, 2010). PBS is generally synthesized through polycondensation of succinic acid and 1,4-butanediol, both of which can be derived from bio-based routes (Xu & Guo, 2010). PBAT is a fossil-based random copolyester composed of adipic acid, terephthalic acid, and butanediol, offering a unique combination of biodegradability, flexibility, and enhanced ductility (Itabana et al., 2024).

The thermal stability, glass transition temperature, and melting temperature of biodegradable polymers are critical determinants of compatibility with specific AM platforms (Shanmugam et al., 2024; Sanchez-Rexach et al., 2020). PLA exhibits a relatively high melting temperature (~150-160°C) and high elastic modulus, contributing to good shape retention and dimensional accuracy in fused deposition modeling (FDM). PCL, with a low melting temperature (~60°C), is ideal for low-temperature processing in biomedical applications. PBAT exhibits excellent elongation and toughness but may require blending with PLA to achieve dimensional stability during processing (Yu et al., 2023).

Biodegradable thermoplastics exhibit distinct degradation mechanisms, rates, and environmental sensitivities (Chamas et al., 2020). PLA and PBS degrade predominantly via hydrolysis of ester bonds, followed by microbial assimilation, while PBAT degrades under enzymatic or oxidative conditions in composting environments. PCL undergoes slow hydrolytic degradation but is enzymatically cleavable in vivo. The rate of degradation is influenced by crystallinity, molecular weight, and environmental conditions such as temperature, pH, and humidity (Laycock et al., 2024).

The integration of biodegradable polymers with AM technologies has demonstrated potential across diverse sectors, including biomedical engineering (resorbable scaffolds and drug delivery systems), packaging (compostable containers), agriculture (degradable seedling pots and mulch films), and consumer products (Lim et al., 2026). AM enables the simultaneous consideration of material composition, structural design, and product life cycle at the design stage—an approach increasingly described as "design for degradation."

2.4 Machine Learning for Surface Defect Detection

Surface defect detection is a common bottleneck in many areas of manufacturing because manual visual inspection tends to be time-consuming and can have inconsistency between human inspectors (Spackman & Butler, 2026). Defects on a surface such as scratches, inclusions, or pits typically lower product quality and significantly reduce product yield. The cost of defects can be much larger if defects were identified early in the production process.

Automated defect detection has advanced significantly with the aid of modern machine learning. Convolutional neural networks (CNNs) in particular have achieved strong performance metrics in defect detection and classification tasks (Jha & Babiceanu, 2023; Yang et al., 2020). However, these high-performing deep learning models also come with drawbacks: they require large labeled datasets, training/inference requires significant computational resources, and they are low in interpretability (Spackman & Butler, 2026).

Classical machine learning pipelines remain relevant in industrial inspection workflows due to their advantages in deployment, maintenance, and interpretability. Feature extraction techniques such as Histogram of Oriented Gradients (HOG), Principal Component Analysis (PCA), and edge detection allow image conversion from unstructured form to forms that can be processed by simple models (Spackman & Butler, 2026). These methods provide the advantages of accuracy, speed, and transparency with the added advantage of being able to process using computing systems that do not have sufficient power to run more complex algorithms.

Research by Spackman and Butler (2026) evaluated multiclass logistic regression in combination with strategically engineered feature extraction as a method to classify defect types in six categories using low-resource computing systems. The combination of HOG and PCA produced the best results, achieving an F1 score of 0.75 on the NEU Surface Defect Database. This demonstrates a significant reduction in misclassifications as compared to single-feature inputs and validates the approach for inspection environments that do not have high-power computing and could benefit from a more transparent interface.

2.5 Manufacturing Engineering Curriculum Design

Manufacturing engineering is becoming increasingly important as more value is placed on supporting the manufacturing sector (Keulen & Sielmann, 2025). The Manufacturing Engineering program at the University of British Columbia is one of only two accredited manufacturing programs in Canada. The program's design spine—a sequence of courses focusing on design education—plays a major role in preparing students for their careers by giving them hands-on application of engineering theory.

The design spine in the Manufacturing Engineering program at UBC consists of first-year introduction to engineering courses, a third-year manufacturing engineering project, and a fourth-year capstone design project (Keulen & Sielmann, 2025). The third-year course involves a two-term long project subdivided into four sub-projects where students work on upgrading a remote-control car using different manufacturing processes. The fourth-year capstone involves industry-sponsored projects where students act as consultants solving real problems.

A comparison of the UBC Manufacturing Engineering design spine to three other curricula (Ontario Tech, CIRP, and University of Michigan) reveals that UBC distributes design content evenly across the years but lacks explicit design instruction in the second year (Keulen & Sielmann, 2025). Student feedback identified opportunities for improvement in clarity of deliverables, project management content, and exposure to more parts of the manufacturing engineering discipline.

The Accreditation Board for Engineering and Technology (ABET) criteria for manufacturing engineering programs require curricular content in materials and manufacturing processes, process/assembly/product engineering, manufacturing competitiveness, manufacturing systems design, and manufacturing laboratory or facility experience (Keulen & Sielmann, 2025). Similarly, the Canadian Engineering Accreditation Board (CEAB) stipulates that specific graduate attributes must be assessed as part of an accredited engineering program, including teamwork, communication, project management, and lifelong learning.

3. Research Methodology

3.1 Research Design

This study employs a comprehensive literature review methodology to synthesize current knowledge on sustainable manufacturing, integrating findings from engineering graphics education, additive manufacturing and life cycle engineering, biodegradable polymers, and machine learning-enabled defect detection. The review follows established guidelines for systematic literature reviews, incorporating both quantitative and qualitative synthesis of peer-reviewed articles, conference proceedings, and industry reports.

3.2 Search Strategy

The literature search was conducted across multiple academic databases including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and ERIC. Search terms were developed based on key concepts identified in the research objectives, including combinations of the following terms: "sustainable manufacturing," "additive manufacturing," "life cycle assessment," "engineering graphics," "technical drawing education," "biodegradable polymers," "surface defect detection," "machine learning," "Industry 4.0," "circular economy," and "design for additive manufacturing."

3.3 Inclusion and Exclusion Criteria

Articles were included if they met the following criteria: (a) published in peer-reviewed journals or conference proceedings; (b) written in English; (c) published between 2014 and 2026; (d) focused on sustainable manufacturing, engineering education, additive manufacturing, biodegradable polymers, or defect detection; and (e) provided empirical evidence, case studies, or comprehensive reviews. Articles were excluded if they were non-peer-reviewed sources, focused solely on non-manufacturing applications, or duplicate publications.

3.4 Data Extraction and Synthesis

Data extraction was conducted using a standardized form capturing article metadata, research objectives, methodologies, key findings, and identified gaps. The synthesis approach employed thematic analysis to identify recurring themes, patterns, and relationships across the literature. Key themes identified included enabling technologies, integration frameworks, implementation challenges, and future research directions.

4. Results

4.1 Engineering Graphics Competency and Manufacturing Performance

The cross-national study by Sarikaya et al. (2026) involving 632 participants across Türkiye, Austria, and Hungary revealed significant gaps in technical drawing competency among engineering graduates. Among the 88 industry professionals surveyed, the most commonly cited weaknesses in new graduates included the inability to accurately interpret production drawings, frequent errors in reading dimensional tolerances and geometric symbols, poor understanding of industrial documentation standards, and time lost to re-training or correcting flawed design inputs.

Figure 1: Proficiency levels of technical drawing skills of new graduates (industry assessment)

Competency Area	Adequate or Higher (%)
Geometric Drawing	40.91%
3D Visualization	38.64%
Sectioning	36.36%
Tolerance Interpretation	26.14%
Standards/Symbol Compliance	14.77%

Source: Adapted from Sarikaya et al. (2026)

The consequences of these skill deficiencies extend beyond individual performance and affect broader production outcomes. Among the 88 industry professionals:

- 79.55% reported production delays attributable to drawing-related errors
- 78.41% reported rework costs
- 73.86% reported scrap generation
- 72.73% reported material wastage
- 62.50% reported time loss due to incorrect assembly

These figures represent the proportion of respondents who endorsed each consequence category, indicating that drawing-related errors are perceived by industry practitioners as a meaningful contributor to manufacturing inefficiency and waste.

When asked which competencies should be prioritized, 73.86% of respondents identified technical drawing standards and symbols as needing the most emphasis, followed by tolerances (69.32%), manufacturing drawings from 3D models (57.95%), and 3D visualization (47.73%). Regarding instructional method preferences, 72.72% of industry respondents favored project-based learning as the most effective approach to enhance technical drawing skills.

4.2 Additive Manufacturing and Life Cycle Engineering Outcomes

The systematic review by Favi et al. (2025) of 87 publications revealed significant variability in the environmental and economic performance of AM technologies. Key findings include:

Energy Consumption: AM technologies generally exhibit higher energy consumption compared to conventional manufacturing. Metal AM processes such as selective laser melting and electron beam melting consume 200-800 MJ/kg of product, compared to 50-200 MJ/kg for conventional machining (Favi et al., 2025). Polymer AM processes such as

FDM consume 16-20 MJ/kg, compared to 10-30 MJ/kg for injection molding.

Material Efficiency: AM enables significant material savings through near-net-shape production. Weight reduction achieved through topology optimization ranges from 15.5% to 80% across case studies (Favi et al., 2025). Part consolidation can reduce component count by 50-80%, eliminating assembly operations and reducing material waste.

Environmental Impact: The global warming potential (GWP) of AM technologies varies widely. For metal AM, GWP ranges from 6-1300 kg CO2-eq/kg depending on the specific technology and life cycle boundaries considered. For polymer AM, GWP ranges from 2.5-1000 kg CO2-eq/kg (Favi et al., 2025).

Economic Performance: AM is cost-effective primarily for low-volume, high-complexity parts or where customization is critical. In mass manufacturing scenarios, traditional techniques such as injection molding or casting continue to outperform AM economically, especially once tooling costs are amortized.

Table 1: Comparative performance of AM technologies

Technology	Material Embodied Energy	Process Energy Consumption	LCA Performance	LCC Performance
FDM	Low-Moderate	Low-Moderate	Moderate	Low-Moderate
SLS	Moderate-High	Moderate	Moderate-High	Moderate
SLA	Moderate	Moderate	Moderate	Moderate-High
L-PBF	High	High	High	High
DED	High	High	High	High
WAAM	Moderate	Moderate-High	Moderate	Moderate
BJ	Moderate	Moderate	Moderate	Moderate

Source: Adapted from Favi et al. (2025)

4.3 Biodegradable Polymers in Additive Manufacturing

The review by Lim et al. (2026) examined the integration of biodegradable polymers with AM technologies, revealing significant opportunities for sustainable production. Key findings include:

Material Compatibility: PLA is the most widely utilized biodegradable polymer in FDM due to its melt stability and high stiffness. PCL is ideal for DIW due to its low processing temperature and moldability. PBAT, with its rubbery nature, is better suited for flexible filament extrusion or co-printing strategies. PBS can be processed via FDM and, when chemically modified, may also be adapted for DLP (Lim et al., 2026).

Degradation Control: Through deliberate structural design and life cycle-oriented engineering, 3D-printed biodegradable systems can be optimized to achieve a balance between mechanical performance and environmental compatibility. Polymer crystallinity, molecular weight, copolymer composition, and composite formulation all influence degradation kinetics (Lim et al., 2026).

Sustainable Design: Design for degradation emphasizes the alignment of material breakdown with the intended functional lifespan of a product. By tuning variables such as crystallinity, copolymer composition, and geometric structure, degradation profiles can be engineered across a broad range of timescales—from weeks to years.

Table 2: Biodegradable polymers in additive manufacturing

Polymer	Bio-based Content (%)	Tm (°C)	Degradation Rate	AM Compatibility	Key Applications
PLA	100	150-160	Slow (months-years)	FDM, DLP	Packaging, consumer goods, scaffolds
PCL	0	60	Very slow (years)	FDM, DIW	Biomedical, drug delivery, wearables
PBAT	0	110-120	Moderate (weeks-months)	FDM, DIW	Packaging, agricultural films
PBS	50	110-115	Moderate (months)	FDM, DIW	Durable goods, automotive, packaging
PHB	100	170-180	Moderate (months)	FDM, SLS	Packaging, agricultural, biomedical

Source: Adapted from Lim et al. (2026)

4.4 Machine Learning for Surface Defect Detection

The study by Spackman and Butler (2026) evaluated a lightweight, interpretable logistic regression pipeline for surface defect classification using the NEU Surface Defect Database. Key findings include:

Feature Configuration Performance: The combination of HOG and PCA produced the best results, achieving approximately 75% overall accuracy and a macro-averaged F1 score of 0.75. HOG alone provided a clear baseline performance improvement compared to raw pixel data (F1 score jumping from 0.30 to 0.61).

Class-Level Performance: Crazing and rolled-in scale achieved higher F1 scores, some exceeding 0.80, suggesting their visual signatures are captured well by gradient-based features. Conversely, scratches were the most challenging class, with F1 scores below 0.50 in some configurations, possibly due to their appearance as small structures with low contrast.

Practical Implications: The approach supports CPU-only deployment and interactive inspection, making it suitable for manufacturing environments with limited computational resources. The proof-of-concept interface built with Streamlit demonstrates how the trained models can be integrated into a workflow operable by manufacturing technicians.

Table 3: Macro-averaged performance across feature configurations

Configuration	Precision	Recall	F1
HOG + PCA	0.76	0.75	0.75
HOG + Edge + PCA	0.73	0.73	0.72
HOG	0.65	0.64	0.63
HOG + Edge	0.63	0.63	0.61
Edge Only	0.36	0.34	0.34
Raw Pixels	0.34	0.32	0.30

Source: Spackman & Butler (2026)

4.5 Manufacturing Engineering Curriculum Design

The curricular review by Keulen and Sielmann (2025) of the Manufacturing Engineering program at UBC revealed both strengths and opportunities for improvement in the design spine. Key findings include:

Design Spine Structure: The program's design spine consists of first-year introduction to engineering courses, a third-year manufacturing engineering project (MANU 330), and a fourth-year capstone design project (MANU 430). The third-year course involves a two-term project subdivided into four sub-projects focused on different manufacturing processes.

Student Feedback: Students identified strengths including exposure to realistic design projects and opportunities for group work and soft skills development. Weaknesses included clarity issues around deliverables and understanding the rubric, as well as uneven contribution among group members.

Curriculum Comparison: UBC distributes design content evenly across years (33% in first, third, and fourth years), while other programs (Ontario Tech, CIRP) load more design content into the fourth year. UBC lacks explicit design instruction in the second year, creating a gap in the design spine.

Proposed Changes: A new second-year course has been proposed to address the gap in the design spine, allowing students to develop design skills continuously through the program and introducing new content to improve student learning experience.

5. Discussion

5.1 Integration of Findings: The Interconnected Nature of Sustainable Manufacturing

The findings from this comprehensive review reveal that sustainable manufacturing requires simultaneous advancement across multiple interconnected domains. The education-industry gap in engineering graphics competency, the environmental and economic trade-offs of additive manufacturing, the potential of biodegradable polymers, and the capabilities of machine learning for quality assurance are not isolated issues but rather interdependent elements of a complex manufacturing ecosystem.

The empirical evidence from Sarikaya et al. (2026) indicates that technical drawing deficiencies are strongly associated with adverse manufacturing outcomes, including scrap generation, production delays, and material wastage. These findings support a compelling association between educational quality in engineering graphics and industrial sustainability outcomes. When graduates produce ambiguous or non-compliant drawings, the resulting scrap, rework, and material waste represent failures of both educational systems and sustainable manufacturing goals.

The integration of biodegradable polymers with additive manufacturing technologies presents significant opportunities for sustainable production. AM enables the fabrication of complex geometries with minimal material waste, while biodegradable polymers provide a pathway to environmentally responsible end-of-life outcomes. However, the realization of these benefits depends on the quality of technical documentation that communicates design intent to manufacturing. If engineering drawings are ambiguous or non-compliant, the sustainability benefits of biodegradable materials and additive manufacturing may be undermined by increased scrap and rework.

The life cycle engineering perspective provided by Favi et al. (2025) underscores the importance of comprehensive assessment of AM technologies. While AM offers significant potential for material efficiency and design flexibility, these advantages are counterbalanced by high energy consumption, material preparation impacts, and post-processing requirements. The development of standardized LCA and LCC frameworks tailored to specific AM technologies is essential for informed decision-making.

5.2 The Role of Engineering Education in Sustainable Manufacturing

The findings from Sarikaya et al. (2026) and Keulen and Sielmann (2025) highlight the critical role of engineering education in enabling sustainable manufacturing. The persistent deficiencies in technical drawing competency among engineering graduates represent a systemic failure of educational systems to develop durable, transferable competencies. When graduates require extensive re-training before they can contribute productively, this represents a failure to develop the foundational skills essential for sustainable manufacturing.

The strong endorsement of project-based learning by industry (72.72%) provides a clear mandate for pedagogical reform. Curricula should be structured around authentic design tasks that simulate the standards, constraints, and feedback loops of real production environments. Project-based learning develops the critical thinking, communication, and standards literacy that employers consistently seek.

The cross-national comparison reveals that effective reform strategies must be locally adapted while drawing on shared international best practices. Austria's stronger digital infrastructure and formalized industry partnerships position it as a potential model for digital integration, yet its students report a paradoxical lack of practical application. Türkiye's industry demand for better graduates creates urgency for change but faces infrastructural barriers. Hungary's vocational sector shows promise through industry support but requires more systematic educator training.

5.3 Life Cycle Engineering as a Framework for Sustainable Additive Manufacturing

The review by Favi et al. (2025) demonstrates that life cycle engineering provides a crucial framework for evaluating and optimizing the sustainability of AM technologies. However, significant gaps remain in the integration of LCE principles into AM design processes. Current design tools—such as 3D CAD, FEM, FEA, and optimization algorithms like topology optimization and generative design—support the creation of lightweight, functionally optimized components. However, the lack of direct integration between these design tools and LCE tools (e.g., LCA and LCC) limits the potential to explore the environmental and economic outcomes of AM-based designs in a life cycle perspective.

The industrial sectors most likely to benefit from LCE-driven AM adoption include aerospace, railway, and public transport—domains characterized by long product lifespans, high utilization rates, and complex, low-volume components. In these contexts, AM enables lightweighting, part consolidation, and decentralized manufacturing, all of which contribute to reductions in emissions, material waste, and logistical burdens.

From a product perspective, those best suited for LCE through AM are typically complex, low-to-medium volume components where weight reduction and customization deliver measurable life cycle benefits. Examples include aerospace brackets, automotive structural parts, and custom medical implants. High-volume, cost-sensitive sectors such as consumer electronics currently find limited advantages in AM due to its higher energy intensity and lack of economies of scale.

5.4 Biodegradable Polymers and the Circular Economy

The review by Lim et al. (2026) positions biodegradable polymers as foundational materials for a new generation of sustainable AM. Their inherent capacity to degrade in response to environmental or biological stimuli, combined with the design flexibility of 3D printing technologies, enables the integration of ecological responsibility with high functional performance.

Design for degradation is a key principle emerging from this work. By tuning variables such as crystallinity, copolymer composition, and geometric structure, degradation profiles can be engineered across a broad range of timescales. Agricultural products benefit from rapid degradation facilitated by polymers such as PBAT or PHBV, while biomedical scaffolds are designed to degrade over several months to support tissue regeneration.

The integration of biodegradable polymers with AM supports the vision of a circular manufacturing model where products are manufactured sustainably, used functionally, and disposed of responsibly. However, challenges remain in material property development, processing compatibility, and regulatory frameworks. The development of next-generation biodegradable polymers that combine structural robustness with controlled degradation behavior will be essential for expanding their practical adoption.

5.5 Machine Learning for Quality Assurance in Sustainable Manufacturing

The work by Spackman and Butler (2026) demonstrates that classical machine learning pipelines remain a practical option for industrial settings where constraints require transparency and low computing power. The combination of HOG and PCA with logistic regression provides a transparent baseline that can be trained, maintained, and debugged without the use of specialized hardware.

The practical implications of this approach are significant for sustainable manufacturing. Automated defect detection enables early identification of quality issues, reducing scrap, rework, and material waste. The CPU-only deployment capability makes the approach accessible to manufacturing environments with limited computational resources. The proof-of-concept interface demonstrates how the trained models can be integrated into a workflow operable by manufacturing technicians.

The comparison to deep learning approaches reveals important trade-offs. While deep learning models achieve stronger performance metrics, their deployment requirements often do not align with industrial environments. Classical pipelines can be a first line of choice when resource constraints are tight, or they can be used as strong baselines to gauge if the added complexity of deep learning would be worth it in a particular environment.

5.6 Toward an Integrated Framework for Sustainable Manufacturing

Drawing upon the synthesis of findings from this comprehensive review, an integrated framework for sustainable manufacturing can be proposed. This framework recognizes that sustainable manufacturing requires simultaneous advancement in human capital development, material innovation, process technology, and quality assurance systems.

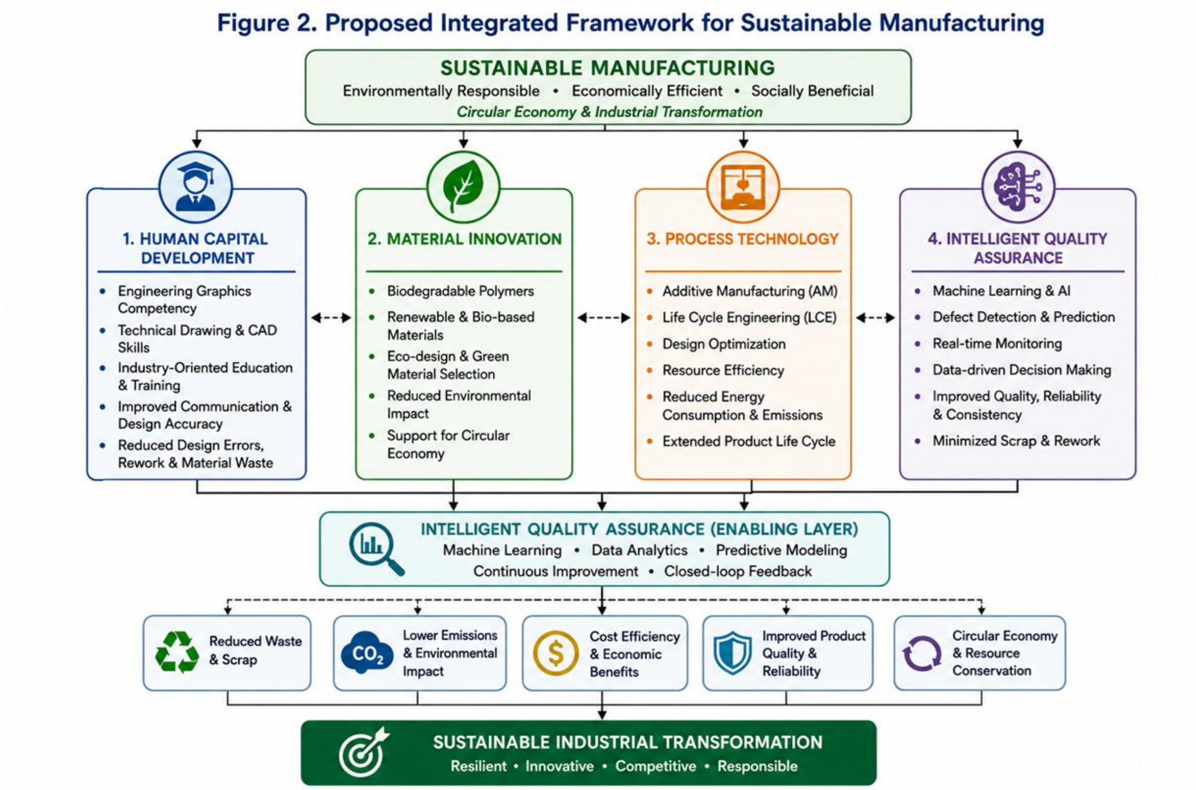
Human Capital Development: Engineering education must evolve to develop durable competencies in technical drawing, spatial reasoning, standards literacy, and design communication. Hybrid pedagogies that balance traditional methods with digital tools, project-based learning, and industry-academia partnerships are essential for bridging the education-industry gap.

Material Innovation: Biodegradable polymers should be selected and engineered to align functional performance with environmental responsibility. Design for degradation principles should guide material selection, composite formulation, and structural design to ensure predictable end-of-life outcomes.

Process Technology: Additive manufacturing technologies should be employed to minimize material waste, reduce energy consumption, and enable on-demand, localized production. Life cycle engineering principles should guide technology selection, process optimization, and design decisions.

Quality Assurance: Machine learning-enabled defect detection should be integrated into manufacturing workflows to enable early identification of quality issues, reducing scrap, rework, and material waste. The selection of appropriate algorithms should balance performance requirements with resource constraints and interpretability needs.

Figure 1. Proposed Integrated Framework for Sustainable Manufacturing



The proposed integrated framework synthesizes the principal findings of this review into a unified conceptual model for sustainable manufacturing. The framework illustrates that sustainable manufacturing is achieved through the interaction of four mutually reinforcing pillars: human capital development, material innovation, process technology, and intelligent quality assurance. Rather than functioning independently, these pillars continuously influence one another. Improvements in engineering education strengthen manufacturing communication and reduce production errors; advances in biodegradable materials support environmentally responsible product design; additive manufacturing and life cycle engineering improve resource efficiency and reduce environmental impacts; and machine learning-enabled quality assurance minimizes defects, scrap, and unnecessary resource consumption. Collectively, these interconnected elements provide a strategic pathway toward environmentally sustainable, economically efficient, and technologically advanced manufacturing systems.

Table 4: Integrated framework for sustainable manufacturing

Domain	Objective	Key Strategies	Stakeholders
Human Capital Development	Develop durable engineering competencies	Hybrid pedagogies, project-based learning, industry-academia partnerships	Educators, industry professionals, policymakers
Material Innovation	Enable responsible material selection	Biodegradable polymers, composite formulation, design for degradation	Material scientists, engineers, product designers
Process Technology	Minimize environmental impact	Additive manufacturing, life cycle engineering, topology optimization	Engineers, manufacturing professionals, facility managers
Quality Assurance	Ensure product quality, reduce waste	Machine learning defect detection, automated inspection	Quality engineers, data scientists, manufacturing professionals

This framework recognizes the interdependencies between these domains. Improvements in engineering graphics education can enable more efficient use of biodegradable materials in additive manufacturing by reducing scrap and rework. Advances in additive manufacturing technologies can expand the applications of biodegradable polymers, creating new markets and driving investment in sustainable materials. Machine learning-enabled quality assurance can provide real-time feedback on manufacturing quality, enabling continuous improvement.

6. Challenges and Future Directions

6.1 Implementation Challenges

Despite the transformative potential of the technologies and approaches reviewed, implementation faces significant hurdles:

Data Security and Cybersecurity: The integration of operational technology with information technology systems creates novel cybersecurity vulnerabilities. Increased digital connectivity in manufacturing environments introduces risks related to IoT devices, cloud systems, and digital twins.

Interoperability and Standardization: The absence of universal communication standards hinders seamless interoperability between different systems and devices. Standardization challenges in additive manufacturing, biodegradable polymer testing, and machine learning deployment require coordinated efforts.

Skills Gap and Workforce Transformation: There is a persistent shortage of workers proficient in both data science and industrial processes. Workforce adaptation to digital transformation requires identifying key competencies and designing upskilling programs.

High Initial Investment and Uncertain ROI: The adoption of advanced manufacturing technologies involves substantial investments in sensors, software, communication infrastructure, and technical training. This is particularly prohibitive for small and medium-sized enterprises.

Data Quality and Reliability: Intelligent systems rely directly on accurate and consistent data to perform precise analyses. Incomplete, inconsistent, or improperly collected information can compromise algorithm performance and lead to incorrect decisions.

6.2 Research Gaps

Based on the comprehensive review of literature, several critical research gaps can be identified:

Integration of LCE with AM Design Tools: The lack of direct integration between design tools and LCE tools limits the potential to explore the environmental and economic outcomes of AM-based designs in a life cycle perspective. Future research should focus on developing and integrating software tools that enable LCA/LCC analysis directly during design.

Standardized Frameworks for AM Sustainability: Existing multicriteria decision-making models show limitations in consistency and often fail to capture the full scope of environmental, economic, and social impacts. There is a critical need for standardized frameworks tailored to specific sectors and production volumes.

Biodegradable Polymer Processing: While biodegradable polymers show promise for AM, challenges remain in material property development, processing compatibility, and regulatory frameworks. Research on next-generation biodegradable polymers that combine structural robustness with controlled degradation behavior is needed.

Machine Learning for Manufacturing: While classical machine learning pipelines show promise for defect detection, further research is needed on robustness, generalization, and integration with manufacturing workflows. Evaluation on multiple sources of production imagery and testing multiscale preprocessing techniques could improve results.

Engineering Education Reform: Longitudinal studies tracking student performance across program cycles, experimental validation of pedagogical interventions, and inclusion of policy-level stakeholders are needed to strengthen the evidence base for curriculum reform.

6.3 Future Research Directions

To address these challenges and gaps, future research should focus on the following directions:

Explainable AI for Manufacturing: Developing AI models whose decisions are transparent and trustworthy to human operators will be crucial for fostering acceptance and enabling effective human-machine collaboration in quality assurance systems.

Edge AI and Real-Time Processing: Pushing more intelligence to the network edge for faster, more autonomous decision-making will enable real-time applications that cannot tolerate cloud latency, particularly important for defect detection and process control.

Human-Centric Automation: Designing systems that augment rather than replace human capabilities is crucial for fostering acceptance and maximizing collaborative potential in manufacturing environments.

Circular Manufacturing: Research on closed-loop systems for biodegradable polymer recovery, including mechanical reprocessing and chemical recycling, will support the transition to circular manufacturing models.

Sustainability Metrics: Developing comprehensive sustainability metrics that integrate environmental, economic, and social dimensions will enable more informed decision-making in manufacturing. The inclusion of well-structured use phase analysis in LCA and LCC models would allow proper evaluation of environmental and cost effectiveness.

Digital Product Passports: Implementing digital strategies for continuous monitoring of component health and integration of digital product passports will enable comprehensive traceability, data-driven decision-making, and optimization of end-of-life processes.

7. Conclusion

This comprehensive review has examined the interconnected pillars of sustainable manufacturing: engineering graphics education, additive manufacturing with life cycle engineering, biodegradable polymers, and machine learning-enabled quality assurance. The synthesis of literature from 2014 to 2026 reveals that sustainable manufacturing requires simultaneous advancement across multiple interconnected domains.

The empirical evidence from cross-national studies indicates that technical drawing deficiencies are strongly associated with adverse manufacturing outcomes, including scrap generation, production delays, and material wastage. These findings support a compelling association between educational quality in engineering graphics and industrial sustainability outcomes. The strong endorsement of project-based learning by industry provides a clear mandate for pedagogical reform, with curricula structured around authentic design tasks that simulate real production environments.

The integration of biodegradable polymers with additive manufacturing technologies presents significant opportunities for sustainable production. AM enables the fabrication of complex geometries with minimal material waste, while biodegradable polymers provide a pathway to environmentally responsible end-of-life outcomes. Design for degradation principles guide material selection, composite formulation, and structural design to ensure predictable end-of-life outcomes.

Life cycle engineering provides a crucial framework for evaluating and optimizing the sustainability of AM technologies. However, significant gaps remain in the integration of LCE principles into AM design processes. The development of standardized LCA and LCC frameworks tailored to specific AM technologies is essential for informed decision-making. The industrial sectors most likely to benefit from LCE-driven AM adoption include aerospace, railway, and public transport—domains characterized by long product lifespans, high utilization rates, and complex, low-volume components.

Machine learning-enabled defect detection offers the potential for automated, consistent, and efficient quality assurance, reducing waste and improving product quality. Classical machine learning pipelines remain a practical option for industrial settings where constraints require transparency and low computing power. The combination of feature engineering with linear models provides a viable alternative to deep learning architectures in constrained manufacturing environments.

The integrated framework proposed in this review recognizes that sustainable manufacturing requires simultaneous advancement in human capital development, material innovation, process technology, and quality assurance systems. The interdependencies between these domains mean that progress in one area can reinforce progress in others.

Looking forward, the convergence of engineering education reform, sustainable material development, advanced manufacturing technologies, and quality assurance systems is poised to play a central role in shaping a sustainable manufacturing ecosystem. Future research should build upon these insights through longitudinal studies, broader geographic coverage, experimental validation of interventions, and inclusion of policy-level stakeholders. By doing so, sustainable manufacturing can reclaim its role not as a static goal but as a dynamic platform for cultivating the engineers, designers, and innovators needed to sustain both professional excellence and environmental responsibility in 21st-century manufacturing.

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