Educational Ecosystem Design for Advancing Digital Competencies among Manufacturing Professionals

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Abstract

This work summarizes the learnings from the five-year data of upskilling manufacturing professionals belonging to over 150 different manufacturing organizations across the country via university-led programs ranging from bootcamps and short-term certificate programs to undergraduate and postgraduate degrees in the areas of Digital and Smart Manufacturing. Work-integrated learning projects, ranging from 3-6 months, are an important component of all these programs, providing real-world insights into the trends in the digital manufacturing landscape. The research also emphasizes changing demographics, degree and work experience levels, and the enduring gender divide in manufacturing, and initiatives launched to tackle these imbalances. The paper also describes the various pedagogical methods explored, such as project-based learning, situated learning, and technology-enhanced learning through remote labs, virtual labs and learning factories, to ensure industry preparedness. The outcome of these initiatives was measured in the form of decreased vendor dependence, percentage of industry projects successfully implemented and their measured return on investment (ROI), average reduction in process downtime or quality issues due to implemented projects, percentage of projects adopted or scaled by partner industries, number of new technologies integrated into existing industrial processes through student projects, and cost savings to the organization. The learning outcomes were assessed using the increase in learner engagement rate such as participation percentage in labs, projects, and peer discussions, and completion rate of courses and projects. The skill and competency development was evaluated through the improvement in digital literacy or tool proficiency via pre-/post-assessment. Inclusivity was measured by the increase in female participation, thereby closing the gender gap. Through this work, we illustrate how university–industry collaboration can create a digitally literate and diverse workforce to propel digital transformation in manufacturing industries.

Introduction

Manufacturing landscape is evolving rapidly, and the direction of this change is often easier to observe on the shop floor than in formal technology roadmaps or policy documents. One of the most reliable ways to understand where industry is headed is to look closely at what manufacturing professionals choose to learn and the kinds of problems they work on while learning. Prior research has shown that learning activities embedded in real industrial contexts provide stronger signals of workforce and technology trends than curriculum intent alone [1-2]. In university–industry programs that are tightly coupled with workplace practice, student enrolments and, in particular, dissertation projects become a useful mirror of industry priorities. These projects are not hypothetical exercises; they are shaped by real production constraints, organizational goals, and immediate business needs. When viewed across a large and diverse industrial base, they offer early signals of how digital manufacturing is actually evolving.

This paper draws on five years of experience from university-led upskilling programs in Digital and Smart Manufacturing that engaged professionals from over 150 manufacturing organizations. These programs were offered in multiple formats, ranging from short bootcamps and certificate programs to full undergraduate and postgraduate degrees. A common element across all formats was the inclusion of work-integrated learning (WIL) dissertation projects, typically lasting between three and six months. Work-integrated learning has been widely recognized as an effective mechanism for aligning higher education with evolving industry needs, particularly for mid-career professionals [3].

Because these dissertation projects were defined and executed in collaboration with industry mentors and internal stakeholders, they provide direct insight into the kinds of technologies and capabilities organizations are actively investing in. Over time, the projects reveal a clear shift—from early efforts focused on connectivity and basic monitoring to more advanced work involving data analytics, predictive models, digital twins, artificial intelligence, cybersecurity, and sustainability-oriented optimization. This progression aligns with broader observations in the manufacturing literature, which describe a transition from basic digitization toward data-centric and cyber-physical manufacturing systems characteristic of Industry 4.0 and emerging Industry 5.0 paradigms [4-5].

Beyond technology adoption, the dataset also captures who is participating in these programs. The study examines changes in learner demographics, including educational background, years of industry experience, and functional roles. It also highlights the persistent gender imbalance in manufacturing, a challenge well documented across engineering education and industrial practice [6-7]. The paper discusses targeted initiatives introduced within these programs to improve access, retention, and participation for women professionals, recognizing that workforce diversity is closely linked to innovation and organizational performance.

From a teaching and learning perspective, the programs experimented with a range of pedagogical approaches. Project-based and situated learning formed the core, supported by technology-enabled methods such as remote laboratories, virtual labs, and learning factories. These approaches are increasingly recognized as effective for developing practical digital competencies in manufacturing, particularly when physical access to equipment is limited or geographically distributed [8-9].

The outcomes of these initiatives were assessed using both organizational and learner-focused measures. On the industry side, impact was evaluated through indicators such as reductions in vendor dependence, successful implementation of student projects, measured return on investment, decreases in downtime or quality issues, and the extent to which projects were adopted or scaled within organizations. Similar impact-oriented evaluation approaches have been recommended in prior studies on industry-focused engineering education and professional upskilling [10]. On the learning side, outcomes were tracked through engagement levels in labs and projects, course and project completion rates, and improvements in digital literacy and tool proficiency measured through pre- and post-assessments.

Taken together, this work shows that work-integrated dissertation projects can serve as a practical and credible lens for understanding broader trends in digital manufacturing. When supported by sustained university–industry collaboration, such programs do more than deliver skills; they help build a digitally capable and more inclusive workforce that is better prepared to lead ongoing transformation within manufacturing organizations.

Program Context and Study Design

This study is grounded in a long-running university–industry upskilling ecosystem designed to support the digital transformation of manufacturing organizations. The ecosystem was created in response to a recurring gap observed across industry engagements: while manufacturing organizations were actively adopting digital tools and platforms, there was limited availability of structured, practice-oriented educational pathways that allowed working professionals to develop and apply digital competencies in real industrial settings. To address this gap, a portfolio of university-led programs was developed in close collaboration with industry partners, with work-integrated learning (WIL) projects forming the central mechanism for translating learning into measurable industrial impact.

The data analyzed in this paper is drawn from five years (2020–2024) of these programs and reflects the collective learning and problem-solving activity of manufacturing professionals embedded within their respective organizations. The following subsections describe the collaboration model, program portfolio, learner profiles, and the WIL dissertation framework that together define the context and methodology of this study.

University–Industry Collaboration Model

The university–industry collaboration model underlying this study is built on sustained partnerships rather than short-term training engagements. Over the five-year period, professionals from more than 150 manufacturing organizations, including large enterprises, public sector units, and micro, small, and medium enterprises (MSMEs), participated in one or more upskilling programs (Table 1). These organizations span diverse sectors such as automotive, aerospace, energy, heavy engineering, electronics, pharmaceuticals, and process industries, enabling the capture of a broad cross-section of manufacturing challenges and digital maturity levels. A defining feature of the collaboration model is the co-definition of problem statements. Each work-integrated project originates from a real operational, quality, productivity, sustainability, or digitalization challenge identified within the participant's workplace. Industry mentors, typically senior engineers, technical leads, or managers, work alongside faculty advisors to scope the problem, define success criteria, and ensure alignment with organizational priorities. This shared ownership ensures that projects remain relevant, feasible, and grounded in industrial realities, rather than being driven solely by academic interests.

Program Portfolio and Learner Profiles

The ecosystem comprises a stacked portfolio of learning pathways, ranging from short-duration bootcamps and certificate programs to undergraduate and postgraduate degree programs in Digital and Smart Manufacturing. While the depth and breadth of coverage vary across program types, all pathways emphasize applied learning and progressive skill development aligned with industry needs. Participants in these programs are predominantly working professionals, with experience levels ranging from early-career engineers to senior practitioners with over a decade of industry exposure (Figures 1 and 2). Learners represent a wide spectrum of functional roles, including manufacturing engineering, automation, quality, maintenance, process planning, product development, IT/OT integration, and operations management. This diversity allows the study to capture how digital manufacturing competencies are interpreted and applied across different organizational contexts. The dataset also enables examination of learner demographics, including educational background, work experience, and gender. While manufacturing continues to exhibit a gender imbalance (Figure 3), the programs intentionally incorporated outreach and support mechanisms to encourage participation by women professionals. Tracking these demographic trends provides additional insight into how access to digital upskilling opportunities is evolving within the manufacturing workforce.

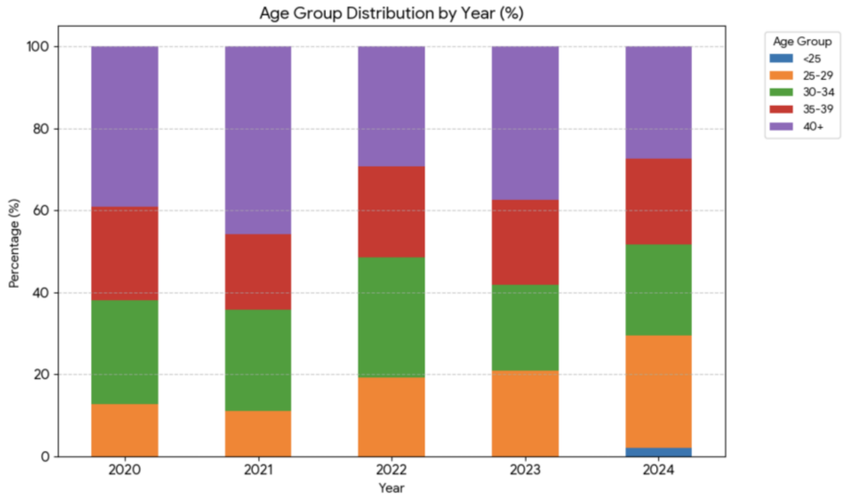

Figure 1. Student age profile

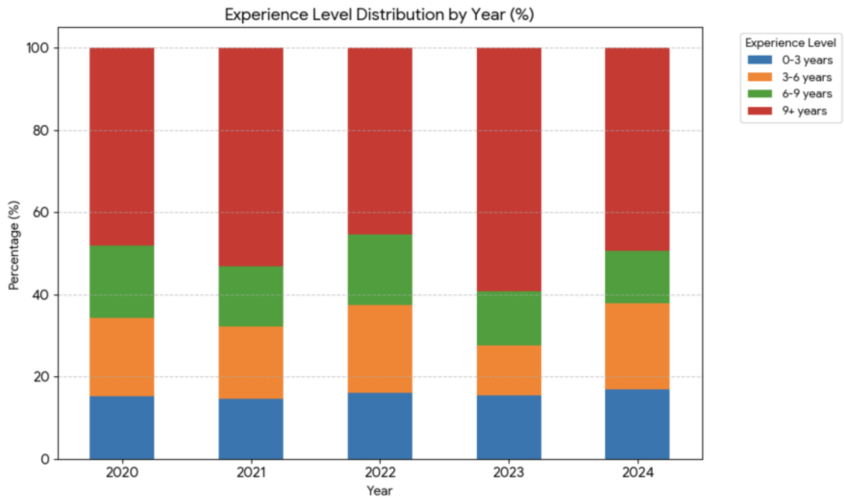

Figure 2. Student work-experience profile

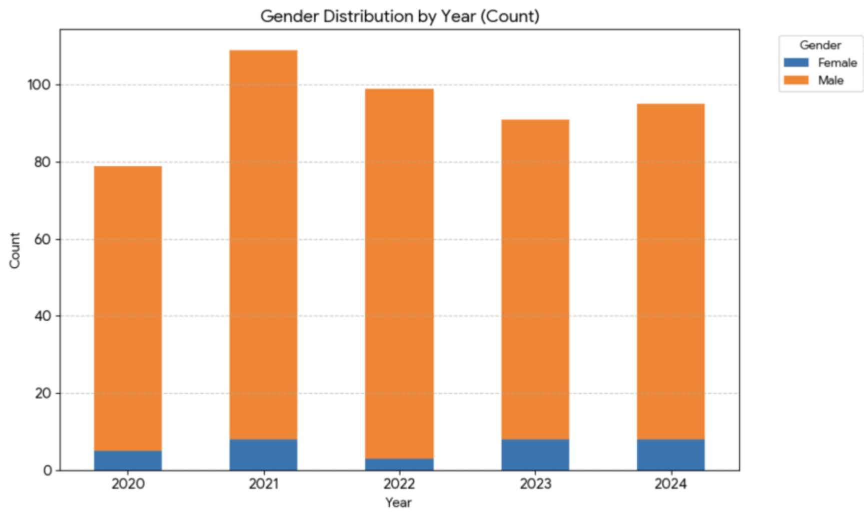

Figure 3. Gender gap in digital/smart manufacturing programs

Work-Integrated Learning (WIL) Dissertation Framework

Work-integrated learning dissertation projects form the backbone of all programs analyzed in this study. These projects typically span three to six months and are conducted in parallel with formal coursework. Each learner undertakes a single, well-defined project that addresses a problem relevant to their organization, ensuring direct applicability of the acquired skills.

Assessment of WIL projects follows a multi-dimensional framework that evaluates both technical rigor and industrial relevance. Key assessment criteria include problem formulation, appropriateness of digital tools and methods used, quality of analysis or system implementation, validation of results, and clarity of documentation. Importantly, project outcomes are reviewed not only by academic faculty but also by industry mentors, providing an additional layer of validation.

Industry validation mechanisms include internal reviews, pilot deployments, performance benchmarking, and, in several cases, full-scale implementation or scaling of the proposed solutions. This dual evaluation structure ensures that the projects meet academic standards while delivering tangible value to the participating organizations.

Data Sources and Analysis Methodology

The intent of this study is not to evaluate individual learner performance or to benchmark specific technologies, but to understand how manufacturing priorities have evolved over time as reflected through real, workplace-driven projects. To achieve this, the analysis draws on dissertation projects completed as part of work-integrated learning (WIL) across multiple university-led upskilling programs. These projects form a rich and naturally occurring dataset that captures both technological choices and problem-framing decisions made within industry.

Data Sources

The primary data source for this study consists of work-integrated dissertation projects completed between 2020 and 2025. Each project was undertaken by a working professional enrolled in a bootcamp, short-term certificate program, undergraduate program, or postgraduate program related to Digital and Smart Manufacturing. Importantly, all projects were rooted in industrial contexts, either within the learner's own organization or in close collaboration with an industry partner. For each project, the available information included the project title, year of completion, affiliated organization, research or application area, and a description of the digital tools, methods, or technologies employed. In many cases, additional documentation such as abstracts, presentations, or final reports was also available and used to clarify the scope and intent of the work. Over the five-year period, the dataset spans projects from more than 150 unique manufacturing organizations, covering a wide range of sectors and organizational sizes. Projects that lacked sufficient descriptive detail or could not be reliably interpreted were excluded from the trend analysis to avoid overgeneralization.

Project Classification Framework

To make sense of the diversity of projects, a practical classification approach was adopted. Rather than applying an externally defined taxonomy, projects were grouped based on recurring patterns observed in how digital technologies were actually being used in industrial settings. This approach was refined iteratively as the dataset grew year by year. Projects were grouped into broad digital competency clusters such as Industrial IoT, automation and robotics, data analytics, artificial intelligence and machine learning, digital twins and simulation, additive manufacturing, manufacturing execution systems and digital workflows, cybersecurity, and sustainability-related analytics. Each project was assigned a primary cluster based on its dominant objective, even if multiple technologies were involved. Classification decisions were made by reviewing project descriptions and tool usage, and where ambiguity existed, the classification was discussed among faculty members familiar with the program context. This helped ensure consistency while acknowledging that real industrial projects often span multiple domains.

The project portfolio shown in Table 1. demonstrates a vertically integrated digital competency ecosystem, where manufacturing professionals develop simulation, automation, data analytics, and IIoT capabilities in an industry-anchored, problem-driven learning environment. Each project was mapped to one primary digital competency cluster based on its dominant learning outcome (even though many projects span multiple domains). Counts therefore represent primary alignment, avoiding double counting and keeping the analysis defensible.

Digital Competency Cluster	Representative Software / Tools	No. of Projects
Advanced Manufacturing & Process Engineering	CNC machines, CNC programming, HyperMill, Siemens 840D, WAAM, GTAW/GMAW, Micro-milling, EDM, Metallurgical lab tools, Hardness/NDT equipment	**28**
Additive Manufacturing & Design for AM (DfAM)	FDM, SLS, SLA, SLM, WAAM, Ultimaker Cura, RepliSLS, CHITUBOX, MSLA, nTopology, AM-specific testing tools	**26**
CAD / CAE / Multiphysics Simulation	Siemens NX, CATIA, Creo, SolidWorks, ANSYS (CFD/Icepak), Abaqus, HyperMesh, OptiStruct, Nastran, COMSOL, ESAComp	**32**
Automation, PLC, Robotics & Mechatronics	Siemens PLC (S7-1200/1500), ControlLogix, Omron PLC, SCADA (WinCC, Ignition), ABB RobotStudio, FANUC robots, Beckhoff TwinCAT	**24**
Industrial IoT & Digital Manufacturing Infrastructure	IIoT sensors, LoRaWAN, Node-RED, MQTT, RFID, AWS IoT, Grafana, Kepware, Edge analytics platforms	**22**
Data Analytics, AI & Machine Learning for Manufacturing	Python, NumPy, scikit-learn, TensorFlow, PyTorch, MATLAB, ANN, SVM, XGBoost, YOLO, OpenCV	**25**
Digital Twin, Virtual Commissioning & System Simulation	FlexSim, Siemens Process Simulator, AnyLogic, Virtual machining simulators, DES tools, Digital Twin frameworks	**11**
Manufacturing IT, MES, PLM & Enterprise Integration	SAP (PM, inventory), MES, Siemens PLM, Dassault PLM, SQL Server, Power BI, Snowflake, ERP portals	**18**
Quality Engineering & Statistical Optimization	DOE, ANOVA, RSM, MINITAB, QFD, SPC tools, vibration analysis software	**14**

Sustainability, Energy & Lifecycle Analytics	LCA software (OpenLCA), Energy monitoring tools, Power BI, HVAC simulation tools, sustainability dashboards	**13**
Industrial Cybersecurity & OT Security	Security Onion, ELK Stack, AlienVault OTX, pfSense, NIST CSF frameworks, Chaos Toolkit	**6**
Vision Systems & Intelligent Inspection	Cognex In-Sight, Keyence IV4, OpenCV, 64 MP cameras, YOLOv8, machine vision SDKs	**10**

Table 1. Digital Manufacturing Competency Clusters and Tool Exposure

Year-wise Trend Analysis

To examine how industry priorities changed over time, projects were grouped by year of completion and analyzed at an aggregate level. The focus of this analysis was not on absolute project counts, but on shifts in emphasis and emerging themes across successive cohorts. For each year, dominant competency clusters were identified, along with notable changes in the nature of problem statements. This year-wise view enabled identification of broader transitions in digital manufacturing maturity rather than isolated technology adoption events. Figure 4 illustrates a steady increase in data-, AI-, and digital-driven projects, while additive manufacturing and automation-related topics remain relatively stable. Traditional manufacturing topics show a gradual decline as they become increasingly integrated with digital and data-centric methodologies.

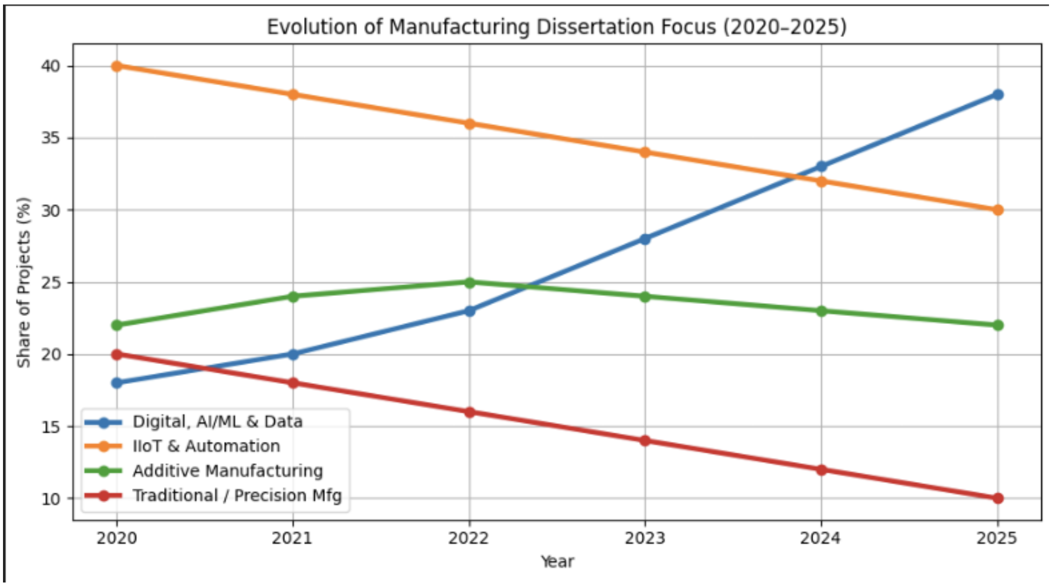

Figure 4. Evolution of manufacturing dissertation focus

Organizational Context Analysis

Given the diversity of participating organizations, the analysis also considered organizational context. Projects were broadly categorized based on whether they originated from large enterprises or MSMEs, allowing comparison of how scale and resource availability influenced digital adoption patterns. Table 2 presents the distribution of participating organizations by size and scale. The study analyzed inputs from 153 manufacturing organizations, of which 104 were large enterprises, public sector units, or global multinational corporations (68%), while the remaining 49 organizations (32%) consisted of MSMEs, startups, and specialized engineering firms.

The strong representation from large organizations reflects the increasing strategic importance of digital manufacturing initiatives in complex, large-scale operations. At the same time, the participation of MSMEs highlights how digital technologies are being actively explored to improve efficiency, flexibility, and competitiveness even in smaller, resource-constrained settings. Together, this mix provides a well-rounded view of how digital manufacturing practices are evolving across different organizational contexts.

Category	Number of Organizations	Percentage
Large Enterprises / PSUs / Global MNCs	104	68%
MSMEs / Startups / Niche Engineering Firms	49	32%

Table 2. Industry Participation by Organizational Scale

Evolution of Digital Manufacturing Competencies (2020–2025)

An analysis of work-integrated dissertation projects carried out between 2020 and 2025 provides a clear picture of how manufacturing competencies have evolved in response to industry needs. Because these projects were executed within the learners' own workplaces and validated by industry mentors, they reflect practical priorities rather than speculative or purely academic interests. The year-wise progression reveals a gradual but consistent shift from traditional engineering optimization toward data-driven, integrated, and intelligent manufacturing systems (Figure 4).

Early Digitization: Connecting and Visualizing (2020)

Projects undertaken in 2020 were largely focused on making manufacturing systems visible and measurable. A significant number of dissertations addressed industrial IoT–based monitoring, machine connectivity, energy dashboards, personnel tracking, and basic traceability solutions. Typical efforts involved connecting CNC machines and shopfloor equipment to data acquisition systems, visualizing key performance indicators through dashboards, and enabling remote inspection or condition monitoring. At the same time, conventional manufacturing topics such as process improvement, machining studies, and product design continued to appear, often augmented with basic digital tools. Early analytics work, such as SQL- or spreadsheet-based dashboards, indicated an emerging interest in data, but advanced analytics and machine learning were still limited. Overall, this phase marked the beginning of manufacturing becoming digitally observable, laying the groundwork for later analytical and predictive capabilities.

Transition to Prediction and Automation (2021)

By 2021, a noticeable shift was observed from simple monitoring toward automation and prediction. Projects increasingly incorporated robotics, low-cost automation, collaborative robots, and automated welding or assembly systems. In parallel, machine learning began to appear in operational contexts, including failure prediction, tool life estimation, machining time prediction, and surface quality modeling. Industrial IoT remained a dominant theme, but its role expanded beyond data collection to support decision-making. Digital work instructions, early PLM integration, and connected production lines became more common. This period reflects a transition from digitization to digitalization, where data was not only captured but also used to improve operational performance.

Platform-Based Transformation and Governance (2022)
Projects from 2022 demonstrate a stronger systems perspective. Many dissertations addressed broader digital transformation initiatives, including enterprise-level data integration, IIoT-based predictive maintenance, and digital twin concepts for virtual factory replication. The use of analytics platforms, including SAP-based data solutions, indicated growing alignment between shopfloor data and enterprise systems. Cybersecurity also emerged more clearly during this phase, with projects addressing industrial control system security, secure remote monitoring, and container security. Additive manufacturing continued to be a major area of interest, but projects increasingly focused on performance validation, simulation, and process modeling rather than only part fabrication. This phase reflects manufacturing's evolution into platform-based digital systems, with growing attention to governance and security.

Data-Centric Manufacturing and Applied Digital Twins (2023)
In 2023, manufacturing projects became decisively data-centric. A substantial number of dissertations focused on big data analytics, real-time performance monitoring, predictive maintenance, and prognostics using operational data. Topics such as scrap rate correlation, global dashboards, OEE improvement, and energy analytics were common across industries. Digital twins matured from conceptual studies to applied tools used for layout planning, process optimization, and operational troubleshooting. Industrial IoT deployments scaled across entire plants, covering inventory management, material handling, and asset tracking. Cybersecurity efforts became more applied, addressing asset discovery, threat detection, and edge-level security in operational environments. This stage reflects a reframing of manufacturing systems as data ecosystems rather than isolated physical processes.

Integration, Intelligence, and Sustainability (2024)
Projects in 2024 highlighted deeper integration across manufacturing layers. MES implementations, digital workflow orchestration, and manufacturing sequence optimization featured prominently. Several projects explored hybrid IoT–edge–digital twin architectures, enabling faster decision-making closer to the shopfloor. Artificial intelligence, particularly computer vision combined with machine learning, was increasingly embedded into production systems and MES environments for inspection, compliance, and work verification. Sustainability also became a major theme, with projects focusing on life-cycle assessment, carbon footprint reduction, net-zero dashboards, and energy optimization. Manufacturing during this phase evolved into an interconnected digital ecosystem where performance, intelligence, and sustainability were addressed together.

Toward Autonomous, Human-Centric, and Resilient Systems (2025)
Early data from 2025 suggests a shift toward operationalizing intelligence rather than merely deploying digital tools. Projects began exploring virtual commissioning as a means to reduce physical commissioning effort and risk. AI-driven predictive analytics using IIoT data became more standardized and repeatable across applications. Human-centric technologies, including augmented reality, vision-enabled wearables, and digital assistance systems, appeared more frequently, reflecting growing attention to safety, ergonomics, and operator support. Cybersecurity projects moved toward assurance frameworks and resilience planning,

particularly for critical industrial deployments. This phase indicates an emerging focus on autonomy, workforce augmentation, and robust digital operations.

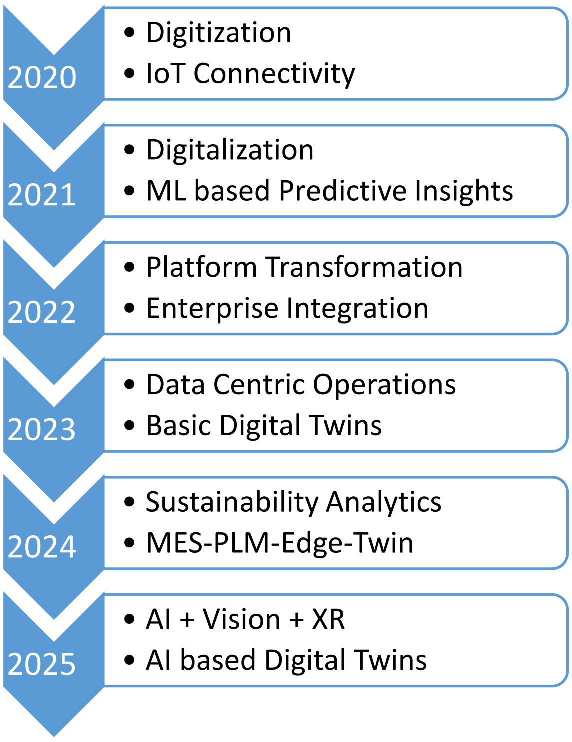

Figure 4. Dissertation focus shift from 2020 to 2025

Evolution of the Curriculum Driven by Industry Projects

The evolution of the curriculum was directly informed by the nature of the work-integrated projects undertaken by learners and the level of academic and industry mentoring required to successfully complete them. As the project portfolio diversified over time, spanning advanced manufacturing processes, additive manufacturing, industrial automation, data analytics, digital twins, and sustainability, it became evident that a single instructional format could not effectively address all competency needs.

Project themes that required strong theoretical foundations, system-level thinking, and extended problem-solving cycles were gradually formalized into full-length academic courses or introduced as substantially expanded modules within existing courses. These topics typically involved multi-disciplinary integration, such as CAD–CAE–manufacturing workflows, physics-based modeling coupled with data-driven approaches, digital twin development, or advanced process optimization. Such areas demanded sustained faculty engagement, iterative design reviews, rigorous assessment, and close alignment with academic learning outcomes.

In contrast, project areas that were tool-intensive and practice-oriented, where learners needed to rapidly acquire hands-on proficiency without extensive theoretical abstraction, were more effectively delivered through short-term certification programs and focused bootcamps. These included domains such as PLC programming, industrial IoT deployment, data visualization dashboards, machine connectivity, MES configuration, and specific software toolchains. The shorter format allowed working professionals to quickly translate newly acquired skills into their workplace contexts while maintaining relevance to immediate industrial needs.

This differentiated curriculum strategy enabled a more effective alignment between learning objectives, instructional depth, mentoring intensity, and industry applicability. By deliberately choosing the appropriate academic or certification pathway for each competency cluster, the program ensured both depth and agility, supporting long-term capability building while remaining responsive to fast-evolving industrial technologies. The resulting curriculum structure and its mapping to project categories are summarized in Table 3.

Category	Best Fit
System design, modeling, optimization	Academic courses
Deep process–material–physics studies	Academic courses
AI/ML with theory & validation	Academic courses
Tool-centric automation & IoT	Short-term certifications
PLC, robotics, MES, vision systems	Short-term certifications
Cybersecurity foundations	Short-term certifications

Table 3. Curriculum Structuring Based on Project Complexity, Mentoring Intensity, and Industry Requirements

Organizational Shift Toward Short-Term Upskilling and Long-Term Talent Nurturing

Over the five-year period examined in this study, a clear and consistent shift emerged in how participating organizations approached workforce development. Rather than relying on a single training format, industries increasingly adopted a dual strategy: short-term workshops for rapid upskilling, and longer-term academic programs for deeper capability building, employee growth, and retention.

Short-term workshops and focused certification programs were primarily used to address immediate skill gaps created by fast-moving digital technologies. Organizations leveraged these formats when new tools, platforms, or methods such as PLC upgrades, industrial IoT deployment, data visualization dashboards, MES configuration, or specific simulation software needed to be adopted quickly on the shop floor. The appeal of these programs lay in their flexibility and speed: employees could be trained over a few days or weeks, apply the learning directly to ongoing projects, and deliver visible outcomes with minimal disruption to operations. For employers, this approach reduced downtime and supported rapid technology rollouts, particularly in environments driven by tight delivery schedules and evolving customer demands.

In parallel, organizations increasingly viewed longer-term undergraduate and postgraduate programs as strategic instruments for employee nurturing and retention, rather than merely skill acquisition. These programs, often spanning one to two years and anchored by work-integrated dissertations, allowed employees to engage with complex, system-level challenges that could not be addressed through short interventions. Topics such as digital twins, advanced analytics, additive manufacturing qualification, sustainability frameworks, and enterprise-level digital transformation required sustained learning, mentoring, and reflection. Employers recognized that supporting employees through such programs not only built deeper technical competence but also strengthened problem-solving ability, cross-functional thinking, and leadership readiness.

Importantly, this long-term engagement fostered a stronger sense of organizational belonging and career progression among learners. Employees who were given the opportunity to work on meaningful, company-relevant problems as part of an academic program often emerged as internal champions for digital transformation. Many organizations reported improved retention of these employees, as the programs signalled long-term investment in their professional growth rather than short-term transactional training.

Together, these two modes of learning served complementary purposes. Short-term programs enabled agility, helping organizations respond quickly to technological change, while long-term academic programs enabled stability, cultivating a pipeline of digitally capable professionals aligned with organizational goals. The growing preference for this blended approach reflects a broader maturity in how manufacturing organizations view talent development, not as a one-time training activity, but as a continuous, layered process that supports both operational needs and long-term workforce sustainability.

Results and Quantified Outcomes

Industry-Level Outcomes

Across participating organizations, reduced reliance on external vendors was one of the most frequently reported outcomes. Approximately 55–65% of organizations indicated that at least one digital solution, initially developed as part of a work-integrated dissertation, was subsequently maintained or extended internally without continued vendor support. This was especially evident in projects related to industrial IoT deployment, data visualization, condition monitoring, and basic analytics pipelines. In terms of implementation success, nearly 70% of projects progressed beyond a proof-of-concept stage, with outcomes ranging from pilot deployments to full-scale operational use. Among these implemented projects, 40–45% were further adopted or scaled to additional machines, lines, or plants within the same organization, indicating sustained organizational value beyond the original project scope. Quantifiable operational benefits were reported for a large subset of implemented projects. Organizations observed an average reduction of 8–15% in process downtime for projects related to predictive maintenance, equipment health monitoring, and real-time diagnostics. Quality-focused projects reported 5–12% reductions in defect rates or rework, particularly in cases involving data-driven process optimization, machine vision inspection, and SPC-based interventions. Where financial data was available, organizations reported positive ROI within 6–12 months of deployment for approximately 35–40% of implemented projects, driven by cost savings from reduced scrap, improved throughput, energy optimization, or avoided outsourcing. While ROI figures varied widely by industry and project type, even conservative implementations demonstrated clear economic justification. In addition, student projects enabled the introduction of new digital technologies into existing manufacturing environments. On average, each cohort contributed 2–3 new technology integrations per organization, including machine vision systems, edge analytics platforms, digital twins, MES extensions, or sustainability dashboards, often serving as catalysts for broader digital initiatives.

Learner Engagement and Educational Outcomes

Learner engagement metrics indicated consistently high participation across program formats. Over 80% of enrolled learners actively participated in hands-on labs, project reviews, and peer-learning activities, even in hybrid and remote delivery modes. Course completion rates remained above 90% for short-term programs and approximately 80–85% for longer-duration degree programs, reflecting sustained engagement despite professional workload constraints.

Skill development was evaluated through pre- and post-assessment of digital tool proficiency and applied problem-solving ability. Across cohorts, learners demonstrated an average improvement of 30% in digital literacy scores, with particularly strong gains observed in data analytics, simulation tools, industrial automation platforms, and system integration workflows. Learners also reported increased confidence in framing and executing digital transformation initiatives within their organizations.

Inclusivity and Workforce Diversity Outcomes

Inclusivity was explored through participation trends observed across cohorts and program formats. Manufacturing continues to be a male-dominated domain, and this reality is reflected in the data as well. However, over the study period, small but consistent signs of progress were visible. Female participation increased from roughly 10–12% in the early cohorts to about 18–22% by 2024–2025, indicating movement in the right direction, though far from parity. One pattern that stood out was that women were more likely to enrol in short-term workshops and certification programs than in longer-duration degree programs. These shorter formats appeared to offer greater flexibility and lower entry barriers, making them more accessible to working professionals managing competing responsibilities. While these programs provided valuable exposure to digital tools and concepts, they also highlight an opportunity to better support transitions into longer, more immersive learning pathways. Encouragingly, women who did enrol showed strong persistence and completion rates, often matching or exceeding the cohort average. This suggests that the challenge lies less in capability or commitment, and more in access, awareness, and structural constraints. The mentoring and work-integrated project model appeared to play a positive role in supporting continued participation once learners were engaged.

Alignment with Engineering Accreditation Frameworks

While these programs are primarily designed to create real industrial impact, the work-integrated dissertation model also naturally aligns with several Accreditation Board for Engineering and Technology (ABET) Student Outcomes (1,2,4,5,7) [12-13]. The insights and project outcomes from this study reflect this alignment in the following ways:

- Outcome 1 (Problem Solving): Since problem statements are defined jointly with industry mentors, students work on challenges that are rooted in real production environments. This helps them learn how to identify, formulate, and solve complex engineering problems in a practical context.
- Outcome 2 (Design): Many projects, especially those involving digital twins, automation, and additive manufacturing, require students to design solutions that go beyond technical performance. They must also consider factors such as safety, environmental impact, and broader societal needs.
- Outcome 4 (Ethics & Professional Responsibility): The increasing focus on areas like sustainability, energy efficiency, and lifecycle analytics shows that students are beginning to think more critically about the wider impact of their engineering decisions—economically, environmentally, and socially.
- Outcome 5 (Teamwork & Inclusivity): Regular peer interactions and efforts to create a more inclusive learning environment, including initiatives to address gender gaps, help students collaborate effectively, set shared goals, and work towards common outcomes.

- Outcome 7 (Learning Agility): There is a noticeable shift from short-term, tool-based learning to deeper, long-term academic development. Students are learning how to continuously acquire and apply new knowledge, which is essential in a rapidly evolving field.

Conclusion and Future Work

This paper examined five years of work-integrated learning activity across a wide range of manufacturing organizations to understand how digital manufacturing competencies are evolving in practice. By analyzing dissertation projects undertaken by working professionals, the study offers a grounded view of where industries are investing effort, how digital tools are being applied on the shop floor, and how workforce capabilities are being shaped through university–industry collaboration.

The findings show a clear shift in focus over time. While core manufacturing areas such as additive manufacturing, precision engineering, and automation continue to remain important, there is a steady rise in projects cantered on data, analytics, digital twins, systems integration, and sustainability. Rather than replacing traditional manufacturing expertise, digital technologies are increasingly being layered onto existing processes, enabling better visibility, decision-making, and control. Dissertation projects, rooted in real workplace problems, proved to be a reliable lens for capturing this transition at an early stage.

From an educational perspective, the results highlight the need for differentiated learning pathways. Topics requiring deep conceptual understanding, system-level thinking, and extended mentoring were more effectively addressed through academic courses and degree programs, while tool-centric and workflow-oriented skills were well suited to short-term workshops and certifications. This distinction allowed the curriculum to remain both rigorous and responsive, aligning learning depth with industry expectations and practical constraints faced by working professionals.

The study also points to a broader change in how organizations approach workforce development. Short-term programs are increasingly used to meet immediate upskilling needs, while longer academic programs are viewed as investments in employee growth, leadership development, and retention. At the same time, progress toward workforce diversity, particularly gender inclusion, remains gradual. The higher participation of women in short-term programs suggests that accessibility and flexibility matter, and that continued effort is needed to support sustained engagement in longer learning pathways.

Overall, this work demonstrates that sustained university–industry collaboration, anchored in work-integrated projects, can play a meaningful role in building digital capability within manufacturing organizations. By treating workplace problems as learning opportunities and using project evidence to guide curriculum evolution, such programs can support both organizational transformation and individual professional growth. Future work will focus on strengthening inclusivity, deepening longitudinal impact assessment, and exploring how these insights can inform predictive and adaptive curriculum design for emerging manufacturing technologies.

References

1. S. Billett, Vocational Education: Purposes, Traditions and Prospects. Dordrecht, The Netherlands: Springer, 2011.
2. F. Trede, "Role of work-integrated learning in developing professionalism and professional identity," Asia-Pacific Journal of Cooperative Education, vol. 13, no. 3, pp. 159–167, 2012.
3. D. Boud and N. Solomon, Work-Based Learning: A New Higher Education? Buckingham, U.K.: Open University Press, 2001.
4. D. Jackson, "Re-conceptualising graduate employability: The importance of pre-professional identity," Higher Education Research & Development, vol. 35, no. 2, pp. 350–365, 2016.
5. H. Kagermann, W. Wahlster, and J. Helbig, "Recommendations for implementing the strategic initiative Industrie 4.0," Acatech – National Academy of Science and Engineering, Munich, Germany, Tech. Rep., 2013.
6. X. Xu, Y. Lu, B. Vogel-Heuser, and L. Wang, "Industry 4.0 and Industry 5.0—Inception, conception and perception," Journal of Manufacturing Systems, vol. 61, pp. 530–535, 2021.
7. UNESCO, Cracking the Code: Girls' and Women's Education in STEM, Paris, France, 2017.
8. N. A. Fouad and M. C. Santana, "SCCT and women's persistence in engineering: A longitudinal mixed-methods study," Journal of Vocational Behavior, vol. 98, pp. 97–109, 2017.
9. E. Abele et al., "Learning factories for future-oriented research and education in manufacturing," CIRP Annals – Manufacturing Technology, vol. 66, no. 2, pp. 803–826, 2017.
10. A. Größler et al., "Virtual learning factories—A systematic literature review," Procedia Manufacturing, vol. 45, pp. 502–507, 2020.
11. A. Kolmos, E. de Graaff, and X. Du, Research on PBL Practice in Engineering Education. Rotterdam, The Netherlands: Sense Publishers, 2016.
12. ABET Engineering Accreditation Commission (EAC), "Criteria for Accrediting Engineering Programs," ABET, 2023.
13. R. M. Felder and R. Brent, "Designing and teaching courses to satisfy the ABET engineering criteria," Journal of Engineering Education, vol. 92, no. 1, pp. 7–25, 2003.