CHALLENGES OF ADOPTING DIGITAL TECHNOLOGIES IN THE MANUFACTURING SECTOR

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Background

The manufacturing industry plays a crucial role in driving UK economic growth, innovation and job creation. It is one of the biggest contributors to the country's economy, accounting for 8.6% of total UK economic output (gross value added) and 8.0% of employment in December 2024 (UK Parliament, 2025). The UK is the 12th largest manufacturing country in the world, and manufacturers are investing £38.8 billion into the UK economy every year (MAKE UK, 2024). It includes several sub-sectors, such as aerospace, automotive, chemical and pharmacy, and food and drinks. The manufacturers also act as a foundational layer in the supply chain for these sub-sectors, underpinning the end-product assembly and delivery.

To remain competitive in the global market, manufacturers continually seek new approaches and techniques to enhance efficiency, lower costs, and deliver high-quality products. The advancements in digital technologies, such as AI, Internet of Things (IoT), and big data, are transforming how these products are designed, produced, and maintained. However, it is challenging for the manufacturing sector to adopt these digital technologies due to barriers such as a lack of skilled workforce, high initial costs and trust and security concerns, as well as insufficient infrastructure (Made Smarter, 2017; Raj et al., 2020; Han et al., 2025; Yilmaz et al., 2023; Schönfuß et al., 2021). By overcoming these barriers to adoption, the UK could move towards highly automated and intelligent manufacturing, eventually becoming a global pioneer in high-value manufacturing. Quantum computing, for example, could accelerate drug discovery for pharmaceutical manufacturing, or enable ultra-secure communication networks for IoT devices. Resolving computational and infrastructural barriers would also unlock smart factories, circular economies, and mass customisation of products (e.g. 3D-printed medical implants) using real-time consumer data.

Current Issues in Adopting Digital Technologies

The main issues regarding the adoption of digital technologies in the manufacturing sector are summarised below:

Lack of skilled workforce:
Designers and engineers are lacking understanding and skills of emerging digital technologies, such as AI. As complexities of products in manufacturing may require different types of digital solutions. Although computerising of manufacturing has been advancing for decades, AI in its current form (LLMs in particular) has only been readily applicable for 2 years at most.

High initial costs:
Lack of a high amount of capital investment in adopting new digital technologies, and lack of awareness of available support and funding access.

Resistance to change:
Manufacturers have performed operations and manufacturing in conventional ways for years, and thereby naturally tend to resist changes.

Unclear return on investment:
It is unclear what the productivity gains and economic benefits are of adopting such digital technologies due to fragmented implementation across the value chain.

Integration challenges:
The current systems may not be compatible with emerging digital technologies, and thereby integrating new technologies with legacy systems can be challenging and costly.

Trust and security:
Trust issues in AI, and other digital technologies such as cloud services, with data privacy and security concerns, which hold manufacturers back from digital transformation.

Limited awareness and knowledge:
Although manufacturers recognise the need to improve productivity and efficiency, they have limited awareness and knowledge of adopting digital technologies.

Lack of infrastructure:
Manufacturers may not have the technological infrastructure needed, such as computing power, to implement new digital technologies

Generic solution unsuitable:
It is challenging to employ off-the-shelf technologies or digital solutions to address a specific problem in manufacturing. There are two reasons for this 1) privacy and 2) relevance to domain knowledge. Training on specific data or fine-tuning is needed when adopting AI technologies and applying them to new problems.

Data imbalance:
Data that is available to manufacturers, may be imbalanced, particularly when capturing data through sensors, which affects training models for deploying industrial IoT systems. Data is the foundation of all AI applications, and poor data makes for poor models.

Opportunities for Digital Transformation

Several opportunities are identified for better supporting the digital transformation in the manufacturing sector:

Transfer learning:
Using knowledge from one model to inform another model, supports the tailoring of solutions to new contexts. A large part of the pre-training process, the creation of "foundation models", is application agnostic. These models can then be further trained for specific problem areas.

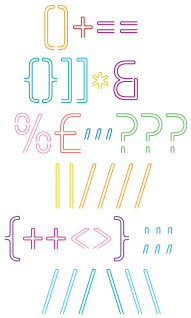
Federated learning:
Sharing model parameters instead of sensitive data to address privacy concerns. Digital transformation introduces multifaceted challenges, including data governance, retention complexities, and privacy risks, which often hinder the success of the transformation (Yilmaz et al., 2023; Schönfuß et al., 2021). These barriers, however, can be mitigated through privacy-preserving machine learning approaches such as federated learning, where model parameters (e.g., neural network weights are shared instead of raw data or entire models. By decentralising training and retaining sensitive data locally, federated learning enables collective model improvement without compromising confidentiality.

Tailored solutions:
Customising readily available AI and digital technologies for solving specific manufacturing needs, for example, using RAG models with domain-specific data.

Data-driven design:
Using data to support innovation of new products, components and systems (Lee & Ahmed-Kristensen, 2025). Decisions at all stages of a product's life-cycle can be informed by data insights analysis, which can then be fed back and used for predictive maintenance or design optimisation.

AI in design:
Applying AI in design and manufacturing to aid decision making, discover new insights and generate ideas (Han et al., 2025). Linked strongly with data-driven design, life-cycle data can be used in conjunction with AI models. Generative models can be used for a variety of activities, including design ideation and product optimisation, or personalisation at scale (Lee & Ahmed-Kristensen, 2025).

Process mining:
Is a critical tool for optimising work-flows by aligning digital transformation with lean principles and sustainability goals. It analyses logs and work-flow data to identify inefficiencies, bottlenecks, and deviations in processes, enabling organisations to streamline operations and establish a leaner foundation for digital transformation (Van der Aalst, 2016). By improving transparency and resource allocation, process mining supports sustainable practices and ensures that digital tools are deployed only where they provide measurable value, avoiding unnecessary technological complexity (Dumas et al., 2018; Lopes de Sousa Jabbour et al., 2020).



Future Developments

Future developments are explored, showing how emerging trends in digital technologies could shape the manufacturing sector's future. These future developments will help the manufacturing sector to benefit from increased productivity and competitive advantage.

Local large language Models (LLMs):
Deploying LLMs locally and integrating with internal databases, through Retrieve Augmented Generation (RAG), enables manufacturers to build secure and customised AI solutions. Such models operate within a company's local environment and thereby maintain data privacy suitable for data-sensitive contexts. Using local data for added domain knowledge can enhance model performance without the need for expensive model (re)training.

Localised cloud storage:
Hosting data via localised cloud services with data governance. Cloud provider like AWS provides such B2B services, enabling local data governance, which may support manufacturers with distributed operations.

Federated learning of distributed manufacturing:
Using LLMs as agents to enable collaborative intelligence, allowing federated learning from local data and exchanging the learning without transferring sensitive data. It can safeguard data privacy for distributed manufacturing operations.

Quantum computing for optimisation:
Quantum computing is emerging as a ground-breaking technology to solve infrastructure and computation challenges at scale. Quantum algorithms can evaluate solutions exponentially faster than classical systems. There are diverse applications and use cases of quantum computing, such as advanced simulations and supply chain optimisations. For example, building companies' data centres to leverage quantum algorithms can help manufacturers advance simulations, optimise supply chains, and accelerate material science.

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