Macrothink Institute™

Business Management and Strategy
ISSN 2157-6068
2026, Vol. 17, No. 1

Transforming the Manufacturing Industry via Large Language Models

Sebastian Quake Sim Ong

Azman Hashim International Business School, Universiti Teknologi Malaysia, Skudai, Johor, Malaysia

Ong Choon Hee (Corresponding Author)

Azman Hashim International Business School, Universiti Teknologi Malaysia, Skudai, Johor, Malaysia

Tan Owee Kowang

Faculty of Management, Universiti Teknologi Malaysia, Skudai, Johor, Malaysia

Lim Kim Yew

Faculty of Business and Communications, INTI International University, Nilai, Negeri Sembilan, Malaysia

Received: January 1, 2026 Accepted: February 14, 2026 Published: March 1, 2026

doi:10.5296/bms.v17i1.23473 URL: https://doi.org/10.5296/bms.v17i1.23473

Abstract

The manufacturing industry is undergoing a critical shift toward digital transformation, in which efficiency, innovation, and responsiveness are central to competitiveness. This paper explores the adoption of Large Language Models (LLMs) such as GPT-4o, Command R+, and DeepSeek-Coder to address existing organizational gaps in data readiness, digital infrastructure, and customer engagement. An organizational assessment reveals limited maturity in analytics, a reliance on manual processes, and minimal customer personalization. To overcome these challenges, the study outlines a strategic vision for achieving excellence and customer centricity enabled by AI. Using the McKinsey 7S framework, the paper highlights misalignments in systems, skills, and structures that must evolve to support transformation. Key focus areas for LLM integration include shop-floor tracking, intelligent production scheduling, compliance documentation, and intelligent customer support. Targeted initiatives such as predictive maintenance, AI-powered search functions, virtual customer assistants, and workforce AI literacy programs are proposed. The paper also addresses risks associated with technical limitations, employee resistance, bias, and data privacy, and proposes mitigation strategies to ensure the sustainable adoption of these solutions. Ultimately, this study demonstrates how LLMs can create a lasting competitive edge in the manufacturing industry.

Keywords: large language models, manufacturing industry, strategic transformation

1. Introduction

The manufacturing industry is entering a new era where efficiency, innovation, and responsiveness are no longer optional; they are essential. Manufacturing, as a highly technical field, requires various technologies to improve efficiency, quality, and innovation capabilities (Bikas et al., 2016). Among the most impactful advancements in this space are large language models (LLMs), advanced AI systems like GPT-4o, Gemini 1.5, and DeepSeek-Coder. These technologies can process vast amounts of information, understand complex language and data, and support a wide range of tasks, from technical document analysis to customer service automation. For manufacturers, the integration of LLMs offers substantial operational value when grounded in economic feasibility and fit-for-purpose model selection. Specialized models, such as Command R+, can enhance regulatory compliance with demonstrated high retrieval accuracy, whereas open-weight options, such as DeepSeek Coder, provide a cost-effective solution for predictive maintenance. Furthermore, deploying high-performance models such as GPT-4o for tender preparation has been empirically linked to reduced operational costs. They can assist engineers in interpreting regulatory standards, support predictive maintenance with intelligent diagnostics, and even streamline the preparation of tenders and quotations. In customer-facing roles, these models can enhance communication, improve responsiveness, and provide accurate information in multiple languages. This paper outlines a clear framework for introducing such technologies into the company's operations. The research methodology starts with an assessment of current capabilities, identifies key areas for improvement, and proposes a phased approach for integrating AI into core functions. The goal is straightforward yet ambitious: to transform digital innovation into a sustainable competitive advantage.

2. Organization Assessment and Gap Identification

It is essential to understand the organization's current standing before planning digital transformation. This section evaluates the company's existing capabilities across technology, people, processes, and data. By identifying strengths and uncovering critical gaps, we can ensure that the transformation strategy is grounded and aligned with business needs.

2.1 Current Status of the Organization

The case company is traditionally rooted in engineering precision, safety compliance, and large-scale manufacturing. It is considered a 3D industry – dirty, dangerous, and challenging. Production processes are conducted continuously, and numerous adjustments can be made to streamline operations and enhance efficiency. The company's digital maturity remains uneven. Below is a closer look at key dimensions of the current organizational state:

2.1.1 Data Readiness

A significant amount of documentation is required for a manufacturing plant, particularly when producing power cables. This includes documents from production logs to safe operating procedures to machine specifications. Currently, these large volumes of documents are stored without a proper structure within the company's server and are not easily accessible for analysis. This limits the organization's ability to perform holistic analytics.

2.1.2 Digital Infrastructure

Currently, the company relies on a legacy ERP system and lacks real-time IoT/AI integration on the shop floor. The company maintains a production logbook for each machine, in which operators are required to record their activities. Supervisors and executives are then supposed to compile reports for each machine and present them regularly, which seems redundant. Additionally, employees within the company spend a significant amount of time monitoring product progress. This is an arduous task because production data may not yet have been updated in the system or may have been entered incorrectly due to human error. Therefore, the most reliable way to track an item's progress is to visit the production floor and observe it firsthand.

2.1.3 Customer Experience

The company's customer engagement model is predominantly transactional, focusing on meeting B2B requirements, including technical compliance, order accuracy, and delivery reliability. While these fundamentals are essential, there is limited emphasis on personalizing customer experience, providing proactive service, or leveraging data-driven customer insights. The use of digital tools to support customer interactions, such as intelligent chat support, self-service portals, or automated proposal generation, remains minimal. As a result, opportunities to differentiate the brand through superior service, responsiveness, or consultative selling are not fully realized. A digitally enhanced approach to customer engagement could help deepen client relationships and improve retention in an increasingly competitive marketplace.

2.2 Latest LLM Development in the Digital Era

2.2.1 GPT-4o

Over the last few years, the advent of Large Language Models (LLMs), such as OpenAI's family (OpenAI, 2023), has significantly advanced the capabilities of Natural Language Processing (NLP). The latest version of GPT-4o (Omni) was released in May 2024, marking a breakthrough in LLM capability by introducing real-time multimodal reasoning across text, images, audio, and video. This model can interpret text-based input alongside visual data, making it particularly powerful in manufacturing environments where visual inspection, machine interfaces, and real-world sensor data play a central role. GPT4 can understand and execute complex instructions, extract valuable insights from large datasets, and facilitate knowledge sharing (Chang et al., 2024). Real-world implementation data shows significant

ROI. For instance, it was reported that a 40% reduction in project delivery time and a 30% decrease in operational costs after integrating GPT-4 for project management and data analysis workflows. Similarly, marketing agencies have documented a 50% increase in content output capacity.

2.2.2 Command R+ (Cohere)

This LLM, developed by Cohere, employs a transformative approach based on Retrieval-Augmented Generation (RAG). This model architecture combines the fluency and reasoning capabilities of LLMs with real-time access to private structured and unstructured data repositories, creating a powerful tool for intelligent information access within industrial environments (Cohere, 2025). Command R+ integrates seamlessly with custom document repositories, enabling it to provide accurate, context-aware answers drawn directly from a company's internal knowledge base. The process of sifting through PDF files, spreadsheets, and data logs could be simplified by this model, which allows users to query these documents in natural language and receive accurate, citation-supported answers within seconds (Lee J. & Su H., 2024). Empirical evaluations suggest that Command R+ offers a viable alternative to larger closed-source models for RAG tasks, specifically by minimizing latency and "hallucination" rates through its specific optimization for retrieval tasks.

2.2.3 DeepSeek Coder

DeepSeek-Coder is an open-source large language model (LLM) specifically developed by the research organization DeepSeek to accelerate software development in technical domains (Deng, Z et al, 2025). It can be used in manufacturing process optimization, enabling engineers to refactor, translate, or document such code, thereby improving maintainability and efficiency. It also supports scripting for simulations and digital twin models, enabling manufacturers to experiment with production variables (e.g. die temperatures, line speeds, or cable cooling profiles) in a virtual environment before applying changes on the shop floor. This reduces downtime and risk while encouraging continuous improvement (Liang W. et al, 2024).

2.3 Gaps Identified

From the above assessment, these are the gaps that were identified in the company case:

a) Limited analytics maturity

b) Lack of AI support in data recording

c) Documents are not searchable or analyzed

d) Manual labor with little to no AI assistance in the production process

e) Lack of AI chat for customer service

3. Vision and Strategic Objectives

A successful digital transformation begins with a clear sense of purpose and direction. This section outlines the company’s vision for how advanced AI and extensive language models can help reshape its operations, customer service, and growth. Alongside that vision are a set of practical, focused objectives designed to turn ambition into action.

3.1 Vision Statement

For the case company, the vision is to lead the current industry through digital manufacturing excellence and customer-centricity, powered by LLMs and AI across the entire value chain.

3.2 Strategic Objectives

a) Implement Shop Floor Tracking (SFT)

Currently, tracking production status, work-in-progress, and bottlenecks requires manual updates or the use of standalone systems. These processes are manually recorded in a book, and a clerk enters the data into an Excel spreadsheet. The objective is to implement AI-driven shop-floor visibility tools that integrate sensor data, machine outputs, and workflow status in real time. This enhances production-line efficiency, supports better planning, and enables faster resolution of issues as they arise.

b) Digitize all engineering and compliance documentation

This action aims to make crucial documents more accessible. By applying LLMs, key details, summaries of lengthy documents, and intelligent search functions, engineers could significantly reduce the time they spend on manual document review and interpretation.

c) Streamline production planning and scheduling with AI

Currently, the Planner's task is to create a schedule that outlines the delivery of an item, while the Production Executive determines which item to run first. This strategy aims to produce dynamic schedules that optimize for throughput, minimize changeover times, and better align with delivery commitments.

4. McKinsey’s 7S Model Diagnosis

The McKinsey 7S Model is used to assess an organization’s readiness for digital transformation and to identify areas where large language models (LLMs) and AI can have the most significant impact. Table 1 illustrates the diagnosis.

Table 1. McKinsey's 7S Model Diagnosis

Element	Present situation	Recommendations
Strategy	Emphasis is given on product and process output, and cost-efficiency	Shift to digital-first, customer-focused growth with LLM-powered innovation.
Structure	Hierarchical structure, which causes slow cross-functional collaborations.	Integrate AI innovation across R&D, operations, and the sales department.
Systems	ERP-heavy, Excel-based analysis	Introduce AI functionality.
Shared values	The focus is given on quality, reliability, and customer trust.	Shared values should evolve to adapt to a changing world as we enter the digital age. Continuous learning and integration with new technologies should be included.
Style	Decision-making is dependent on senior management. This limits efficiency and adaptability.	An empowering style should be adopted to encourage middle managers, engineers, and operators to take the initiative.
Staff	Proficient in manual labor but with low digital fluency.	Provide training for operators to be tech-savvy.
Skills	Strong capability in machine handling and mechanical knowledge.	Integrate AI, automation and machine learning to enhance efficiency.

The analysis indicates that, while the company is operationally strong, it is digitally underdeveloped. Key gaps exist in systems integration, digital skills, and strategic alignment around AI technologies. Structure and style must adapt to modern changes to support cross-functional agility, while values and leadership must embrace continuous learning and experimentation to drive innovation.

5. Key Focus Areas for LLM Adoption

To implement digital transformation, the adoption of Large Language Models (LLMs) presents an excellent opportunity to enhance operations, drive innovation, and elevate customer experience. This adoption should be implemented in areas where it can solve real-world problems, unlock efficiencies, and support strategic goals.

Below are the key areas that have been identified:

5.1 Shop Floor Tracking (SFT) and Reporting

The integration of LLMs could provide clear shop floor visibility and exception reporting. The manufacturing plant generates a substantial volume of data; however, much of it remains underutilized. LLMs can convert raw data into reports for executives, highlighting issues such as setup time, idle time, downtime trends, or even quality rejections. Additionally, LLMs can display items on the production floor and indicate which machines are in operation. The factory is large, and it can be challenging to locate a specific item on the factory floor and to monitor the machines that are running. LLMs can save employees time and effort when tracking them.

5.2 Intelligent Production Planning and Scheduling

Material constraints, equipment availability, and urgent order changes often disrupt production planning and scheduling. By combining LLMs with predictive analytics and real-time shop-floor data, the company can generate dynamic production plans and receive instant, natural-language explanations of scheduling conflicts or bottlenecks. This enables planners to make faster, more informed decisions and enhances overall production efficiency.

5.3 Technical and Compliance Documentation

The manufacturing plant requires strict adherence to national and international standards, and managing this compliance involves reviewing and interpreting large volumes of technical documents. LLMs can be deployed to extract relevant compliance clauses, summarize regulatory changes, and verify the alignment of internal documents with certification standards. This not only improves accuracy but also reduces the time engineers spend manually navigating and complying with requirements.

5.4 Smart Customer Support

In an industry where clients often seek custom specifications or clarification on technical matters, the ability to respond quickly and accurately is a competitive advantage. LLM-powered chatbots and virtual assistants can handle a wide range of queries in real time—offering product recommendations, explaining cable characteristics, or generating datasheets and installation guides. This enhances customer satisfaction while freeing up technical staff for higher-value tasks.

6. Key Initiatives and Interventions

To drive successful LLM adoption and extract measurable value across the enterprise, a set of targeted initiatives and interventions is proposed for the implementation roadmap. These initiatives are structured to align with strategic objectives, including enhancing productivity, optimizing operations, and fostering innovation across engineering, production, quality, and customer service.

6.1 Shop Floor Assistance & Automation

This initiative targets the core of the company, specifically production. If the production operation can be optimized, the company will be more productive, and management will have time to focus on minor problems.

Interventions:

a) Deploy DeepSeek-Coder for generating or assisting with ladder logic and structured text programming for PLCs in extrusion lines, testers, and material handling units.

b) Use LLMs to generate a production schedule based on the delivery date and machine capacity.

c) Support predictive maintenance by automating the analysis of equipment logs and generating maintenance schedules.

Expected outcomes:

a) Improved traceability of quality metrics linked to production cycles.

b) Lower machine failure rates and better OEE (Overall Equipment Effectiveness).

6.2 LLM-Powered Search Function

Retrieval-augmented models, such as Cohere's Command R+, can be employed to build intelligent search and Q&A systems that operate across internal repositories.

Interventions:

a) Integrate Cohere Command R+ with internal documentation such as SOP, product specifications, ISO certifications, and machine specifications.

b) Build intelligent Q&A systems for engineers, QA officers, and compliance auditors to extract accurate information on demand.

Expected outcomes:

a) Reduced time spent searching for critical documents.

b) Improved knowledge transfer across departments and shifts.

6.3 Smart Customer Service & Quotation Support

In the competitive B2B manufacturing landscape, customer responsiveness and technical support are critical differentiators. Therefore, this initiative aims to provide 24-hour automated customer support and ensure consistent, high-quality communication with clients.

Interventions:

a) Deploy LLM-based virtual assistants such as GPT-4 into CRM systems and customer portals to support product queries and status updates for order delivery.

b) Enable rapid access to product catalogs, pricing, and order histories.

Expected outcome:

a) Improved customer satisfaction and engagement.

b) Increased quotation accuracy and conversion rates.

6.4 Increase Workforce AI Literacy & Capability

This intervention aims to create sustainability within the company’s workforce. To ensure the successful adoption of AI within the company, employees should receive support and training to develop their AI literacy.

Interventions:

a) Launch in-house AI training program

b) Establish an AI support committee to coach and provide support to employees.

Expected outcomes:

a) Higher employee adoption and trust in AI tools.

b) Keep up with the age of digitization by having a strong digital culture and an innovative mindset.

7. Risk and Mitigation Plan

The integration of Large Language Models (LLMs) into a manufacturing organization's operational and strategic workflows introduces significant opportunities for innovation, efficiency, and competitiveness. However, it also presents a variety of risks that must be carefully managed to ensure successful implementation. This section outlines key risk categories, operational constraints and proposes a structured mitigation plan to address each challenge proactively.

7.1 Technical & Resource Limitations

Deploying LLM technologies often requires substantial computational infrastructure, specialized software integration, and access to high-quality data. Legacy ERP/ MES systems prevalent in the power cable industry often lack the necessary interoperability to work seamlessly with AI tools.

Mitigation Strategies:

- Conduct a digital infrastructure audit to assess hardware and system readiness.
- Phase implementation to start with low-risk, high-impact use cases (e.g., document search, quotation automation) before expanding into core manufacturing processes.
- Partner with AI solution vendors or managed service providers for scalable support.

7.2 Employee Resistance

The adoption of AI tools may trigger resistance from employees who fear job displacement, increased complexity, or a lack of familiarity with digital technologies. In a traditionally conservative industry such as power cables, cultural inertia can impede transformation. (Khaw et al., 2022) argues that change increases stress and decreases commitment and loyalty.

Mitigation Strategies:

- Introduce structured change management programs, including frequent communication and employee engagement sessions.
- Provide hands-on training, role-specific AI literacy workshops, and certification programs to increase user confidence.
- Highlight how LLMs enhance rather than replace roles, for example, reducing manual documentation or supporting decision-making.

7.3 Bias in AI Models

Bias is defined as a systematic error in decision-making processes that results in unfair outcomes (Ferrara, 2024). LLMs may produce outputs that are factually incorrect, misleading, or biased if the model is not adequately trained on industry-specific data or if contextual limitations are not properly accounted for. This can pose serious risks in engineering, safety, and compliance-critical contexts. Researchers and practitioners have proposed various mitigation strategies, such as improving data quality (Asan et al., 2020) and designing explicitly fair algorithms (Friedler et al., 2019).

Mitigation Strategies:

- Use retrieval-augmented generation (RAG) approaches to combine LLMs with trusted internal knowledge bases and technical documentation.
- Implement human-in-the-loop (HITL) workflows for validation of outputs, especially in quality control, compliance, and engineering design tasks.
- Establish a feedback loop to fine-tune the model based on usage data and correction patterns.

7.4 Data Privacy Concerns

Integrating LLMs with production data, customer contracts, and proprietary cable designs raises concerns about data privacy, compliance (e.g., GDPR, PDPA), and intellectual property protection, particularly when using third-party or cloud-based models.

Mitigation Strategies:

- Adopt strict data governance policies, including encryption, role-based access controls, and anonymization of sensitive information.
- Favor open-source or private LLMs (e.g., on-premises versions of LLaMA, Mistral, DeepSeek) for sensitive tasks.
- Require vendors to comply with industry-standard security certifications (ISO/IEC 27001, SOC 2) and include data protection clauses in contracts.

8. Conclusion

The integration of Large Language Models (LLMs) into the manufacturing industry represents a transformative opportunity to overcome long-standing inefficiencies and strengthen competitiveness in an increasingly digital economy. This paper demonstrates how LLMs can address critical organizational gaps by enhancing data accessibility, automating shop floor tracking, streamlining production planning, simplifying compliance, and improving customer service. Through strategic objectives, targeted initiatives, and a phased roadmap, the company can transition from manual, fragmented processes to an intelligent, connected ecosystem that supports innovation and growth. While challenges such as technical limitations, employee resistance, bias, and data privacy concerns remain, proactive risk mitigation and workforce upskilling will be essential in ensuring the sustainable adoption of these solutions. Nevertheless, governance and accountability concerns must be addressed by a robust strategy centered on data sovereignty, algorithmic traceability, and safety oversight. Furthermore, to mitigate operational risks, a strict Human-in-the-Loop (HITL) protocol is mandated, treating LLMs as decision-support tools and assigning certified engineers' final liability for all safety-critical interventions. Success will ultimately depend on cultivating a culture of continuous learning and digital fluency throughout the organization. By embedding AI at the core of its operations and decision-making, the organization can achieve greater efficiency, agility, and customer centricity, thereby positioning itself as a leader in digital manufacturing excellence.

Acknowledgments

Not applicable.

Authors contributions

Not applicable.

Funding

This publication was financially supported by the Norwegian University of Science and Technology (NTNU) (Vot: 4C586).

Competing interests

Not applicable.

Informed consent

Obtained.

Ethics approval

The Publication Ethics Committee of the Macrothink Institute.

The journal's policies adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

Provenance and peer review

Not commissioned, externally double-blind peer reviewed.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data is not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data is available.

References

Asan, O., Bayrak, A. E., & Choudhury, A. (2020). Artificial intelligence and human trust in healthcare: A focus on clinicians. *Journal of Medical Internet Research*, *22*(6), e15154. https://doi.org/10.2196/15154

Bikas, H., Stavropoulos, P., & Chryssolouris, G. (2016). Additive manufacturing methods and modeling approaches: A critical review. *The International Journal of Advanced Manufacturing Technology*, *83*, 389–405. https://doi.org/10.1007/s00170-015-7576-2

Chang, Y., Wang, X., Wang, J., Wu, Y., Zhu, K., Chen, H., … & Wang, Y. (2024). *Large language models for manufacturing*. arXiv. https://arxiv.org/abs/2410.21418

Cohere. (2025, June 10). *Command R+ model*. Cohere Docs. https://docs.cohere.com/v2/docs/command-r-plus

Deng, Z., et al. (2025). Exploring DeepSeek: A survey on advances, applications, challenges and future directions. *IEEE/CAA Journal of Automatica Sinica*, *12*(5), 872–893.

Ferrara, E. (2024). Fairness and bias in artificial intelligence: A brief survey of sources, impacts, and mitigation strategies. *Sci*, *6*(1), 3. https://doi.org/10.3390/sci6010003

Friedler, S. A., Scheidegger, C., Venkatasubramanian, S., Choudhary, S., Hamilton, E. P., & Roth, D. A. (2019). A comparative study of fairness-enhancing interventions in machine learning. In *Proceedings of the Conference on Fairness, Accountability, and Transparency* (pp. 329–338). ACM. https://doi.org/10.1145/3287560.3287596

Khaw, K. W., Alnoor, A., Al-Abrrow, H., Tiberius, V., Ganesan, Y., & Atshan, N. A. (2022). Reactions towards organizational change: A systematic literature review. *Current Psychology*, *42*, 19137–19160. https://doi.org/10.1007/s12144-022-03070-6

Lee, J., & Su, H. (2024). A large unified industrial knowledge. *International Journal of AI for Material and Design*, *1*(2), 3681.

Liang, W., et al. (2024). *DeepSeek-Coder: When the large language model meets programming—The rise of code intelligence*. arXiv. https://arxiv.org/abs/2401.14196

OpenAI. (2023, November 17). *Introducing ChatGPT*. OpenAI Blog. https://openai.com/blog/chatgpt