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Digitalisation: The Missing Step Before AI in Industry 4.0

Seok Peng Ngan[a], Sue Lin Ngan[b], Donghui Zhao[b], Hon Loong Lam[a,*]

[a]Department of Chemical Engineering, The University of Nottingham Malaysia, 43500 Jalan Broga, Semenyih, Selangor, Malaysia
[b]UKM-Graduate School of Business, University Kebangsaan Malaysia, 43600 UKM, Bangi, Selangor, Malaysia
Honloong.lam@nottingham.edu.my

Artificial intelligence (AI) has emerged as a game-changer across industries in the rapidly evolving digital landscape. Industry experts have started AI implementation and believe AI is the transformative force that can revolutionise Industry 4.0. However, the results and impacts are questionable as data fragmentation, inefficient decision-making, and operational bottlenecks persist even with AI implementation. It leaves the stakeholders hesitating if AI is the key to unlocking the potential or improving Industry 4.0. Digitisation, which systematically transforms traditional processes, data, and systems into digital formats, lays the groundwork for broader technological transformation. Digitalisation, in turn, takes a more integrated approach by utilising digital data and technologies to reshape business operations and streamline workflows. Both digitisation and, more significantly, digitalisation have been recognised as essential enablers for successful AI implementation. However, the significance of digitalisation remains a question, as some stakeholders consider it to be an optional step instead of a prerequisite for AI. Without a mature digital ecosystem, AI-driven solutions often face inefficiencies, including delayed and inaccurate data processing, as well as redundant workflows that result in misleading insights. This work employs the Six Sigma methodology, often known as DMAIC (Define, Measure, Analyse, Improve, Control) methodology, to systematically assess the necessity of digitalisation prior to AI adoption. A case study in the manufacturing industry is presented to illustrate the gaps or limitations of implementing AI without a mature digital ecosystem. The application of the Six Sigma methodology defines key challenges in non-digitalised manufacturing environments, measures performance disparities, analyses root causes of AI failures, improves AI integration through structured digital transformation, and finally establishes control mechanisms for sustainable AI-driven operations. The findings reflect that a well-established digital ecosystem is critical for AI success. This work provides a strategic framework for policymakers, businesses, and industries as a guide for improving the digitalisation process and maximising AI's potential in the future.

1. Introduction

Over the past decade, the Fourth Industrial Revolution, commonly denoted as Industry 4.0, has reshaped the global industrial landscape through the convergence of advanced digital technologies. The advent of intelligent automation that utilises artificial intelligence (AI), business process management and robotic process automation to streamline and scale decision-making across organisations has marked a new chapter in industrial 4.0 development (Attaran Mohsen, 2023). Among major elements in intelligent automation, AI stands at the forefront of this transformation and is often perceived as the primary driver of innovation and efficiency across various industries. It acts as the central coordinator that connects and interprets data from diverse technologies (i.e., Internet of Things (IoT), cloud computing, robotic process automation).Deep learning, a subset of machine learning within the broader domain of AI plays a significant role in enabling machines to access and learn from a wide range of data sources and further employs multilayered neural networks to identify complex patterns that accelerate the learning process (Ross and Jess, 2022). The capabilities of machine learning contribute to the advancement in artificial intelligence by allowing machines to become more adaptive and intelligent. The ability of AI to mimic cognitive functions, process vast amounts of data, and later generate actionable insights in real-time has encouraged practical applications in industries (i.e. predictive maintenance, autonomous production systems, intelligent supply chains, adaptive quality control) with minimal human

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intervention. As a result, leading technology organisations such as Amazon, Microsoft, Google and IBM are actively developing advanced AI solutions tailored to industrial applications, positioning AI as a strategic enabler of innovation for greater efficiency and long-term competitiveness. Meanwhile, governments across the world (i.e., European Union, Norway, and Switzerland) have also taken the initiative to integrate AI into national agendas, mainly to support improving public service delivery as well as enhancing internal management resilience in an increasingly dynamic global economy (Van Noordt and Misuraca, 2022).

Despite the growing integration of AI in industrial and government settings, AI implementation efforts continue to face issues such as data quality and security, operational disruptions, as well as ethical concerns and regulations (Kejriwal, 2023). One of the key factors that leads to the shortcomings is the lack of a mature digital ecosystem. It brings the role of digitalisation into the centre of attention, not merely as a supporting element but as a potentially essential prerequisite for AI to perform effectively over the long run. This study aims to introduce the Six Sigma DMAIC (Define, Measure, Analyse, Improve, Control) methodology to systematically assess the necessity of digitalisation prior to AI adoption, exploring whether the progress of digitalisation in an organisation fundamentally limits the performance and scalability of AI. Six Sigma was developed in the 1980s by engineers Bill Smith and Mikel Harry at Motorola as a quality management tool that can reduce waste and variation within a system using data and continuous quality improvement (Rosing et al., 2015). However, Rosing et al. (2015) also highlight the fact that implementing the Six Sigma framework was uncommon until General Electric (GE) adopted the framework in the 1990s under the leadership of Jack Welch, officially marking a turning point for Six Sigma in the history of process improvement. DMAIC is the core data-driven, systematic step-by-step methodology in the Six Sigma framework to identify and eliminate defects and reduce process variation. In essence, DMAIC follows the methodology sequence by defining the issues, measuring and assessing the current performance, analysing root causes, implementing solutions, and ensuring long-term improvements. Even though DMAIC was initially applied in the manufacturing industry, it has since been adopted across various industries (i.e., healthcare, finance, services) for its effectiveness in solving complex operational challenges and continuous improvement (Gagnon, 2022). A case study from the manufacturing industry is presented to demonstrate the practicality of applying the DMAIC methodology in examining the gaps of AI implementation in the absence of a robust digital ecosystem. The rest of the paper is structured as follows: Section 2 – Defining the Digital Ecosystem: A conceptual and relational review; Section 3 – Methodology - Analysing AI Implementation Gaps using DMAIC; Section 4 – Case Analysis and Discussion; Section 5 – Conclusion - Prospect, recommendations, and future works.

2. Defining the Digital Ecosystem: A conceptual and relational review

Understanding the concepts of popular terms, including digitisation, digitalisation, Industry 4.0, and AI, is essential to contextualise the interrelationship and relevance in defining a digital ecosystem. Digitisation is a technical process of transforming information from analogue to digital formats (i.e., scanning paper documents into PDF files, vinyl records into MP3 audio files). It is imperative to recognise that digitalisation cannot occur without digitisation, as digitalisation builds upon digitisation and involves the use of digital data and technologies to reshape business operations, improve stakeholder interaction, and streamline workflows (Holmström, 2022). A study by Truant et al. (2022) emphasises that digitalisation not only utilises digital data and technologies to change an organisation's business model but also provides opportunities to improve its value creation path. The transformative shift in business model brought about by digitalisation aligns with the core concept of Industry 4.0, which envisions a highly connected, intelligent production environment through the convergence of digital technologies (i.e., AI, IoT, big data analytics, cloud computing) that drive efficiency and innovation (Javaid et al., 2022). The significance of digitalisation is further highlighted as it has been described as "the fourth industrial revolution" in the World Economic Forum due to its immense potential impact on consumers, societies, and businesses (Hossnofsky and Junge, 2019).

On the other hand, AI also emerges as a game-changer that can fulfil the ambition of Industry 4.0. Kejriwal (2023) defines AI as a collective of digital technology components, including natural language processing, machine learning, algorithms, and others, that enable computers and machines to simulate human learning (i.e., comprehension, problem-solving, autonomy). However, the full potential of AI can only be unleashed under the assumption that AI operates within a well-structured and integrated digital ecosystem, which is highly dependent on the level of digitalization (Ross and Jess, 2022). Within a digital ecosystem, AI can leverage the digital data to perform functions such as pattern recognition, prediction, optimisation, and even autonomous decision-making. In essence, the progression from digitisation to digitalisation lays the essential foundation for building a robust digital ecosystem, which is critical for enabling advanced AI capabilities. The synergy between digitalisation and AI has become increasingly inevitable, considering broader societal and industrial trends are driving organisations toward more dynamic, data-driven, and autonomous environments (Kejriwal, 2023). The integration ultimately enables the realisation of the industry 4.0 vision, creating intelligent systems that move beyond basic automation to interconnected technologies and processes that can continuously adapt and optimise operations.

While AI is widely recognised as a critical driver of innovation in today's digital era, its adoption does not always yield positive outcomes. Lui et al. (2022) highlights that AI investment can have a negative impact on an organisation's market value, particularly for organisations with weak information technology (IT) capabilities. Weak IT capabilities refer to an organisation's limited capacity to manage, integrate, and utilise digital systems and data effectively and efficiently (references). When an organisation publicly commits to AI investment without the necessary digital infrastructure and technological readiness to support the initiatives, issues such as operational disruptions and the failure of AI initiatives to meet stakeholder expectations can arise, which in turn may lead to declining stock prices and reduced investor confidence. Meanwhile, organisations with low levels of digitalisation tend to face reputational damage and organisational resistance due to unmet expectations and poorly integrated AI initiatives that fail to deliver promised efficiencies. The findings suggest that the success of AI implementation is not determined solely by AI technologies but is also highly influenced by the organisation's level of digitalisation, sometimes referred to as digital maturity. The digital maturity of an organisation is closely tied to the information technology capabilities to manage, integrate, and utilise data effectively. While there is a clear correlation between digitalisation and AI, both digitalisation and AI are often treated as separate initiatives in practice and literature, leading to a popular ongoing debate around the extent to which an organisation's digital maturity shapes the outcomes of AI implementation (Perifanis and Kitsios, 2023). IBM Watson Health and Amazon, offer valuable insights into how different levels of digitalisation can yield varying outcomes when it comes to AI implementation. The $4B failure of IBM's Watson for Oncology, an AI system designed to help doctors diagnose and treat cancer, alarms stakeholders and investors regarding the practical functionality of AI and highlights the importance of a mature digital ecosystem. Despite its advanced AI capabilities, IBM Watson for Oncology struggled to deliver reliable treatment recommendations and adapt to the clinical complexities of the healthcare industry, primarily due to the lack of comprehensive, high-quality clinical data and poor integration with hospital information systems (Gagnon, 2022). Without a mature digital ecosystem that includes a modern, connected data infrastructure capable of supporting real-time operations and predictive analytics, the potential of even the most advanced AI technologies is compromised. In contrast, Amazon presents a strong example of successful AI implementation in the supply chain and logistics sectors. Backed by a high level of digitalisation, Amazon leverages integrated data platforms, real-time IoT-enabled supply chains, and cloud infrastructure to enhance AI-driven capabilities in functions such as optimising inventory management, forecasting consumer demand, and streamlining delivery operations (McKinsey & Company, 2025). The IBM Watson Health and Amazon cases illustrate that without a mature digital ecosystem, AI implementation often results in high costs and limited or negative productivity. In contrast, digitally mature organizations are better equipped to achieve impactful and sustainable AI outcomes.

3. Methodology - Analysing AI Implementation Gaps using DMAIC

In this study, the Six Sigma DMAIC methodology serves as the primary mechanism to examine how different levels of digitalisation influence AI performance in the manufacturing industry within the industry 4.0 context. As illustrated in Figure 1, the DMAIC framework provides a five-phase process improvement cycle, namely Define, Measure, Analyse, Improve, and Control, that offers a structured and process-oriented approach to identify the root causes of inefficiencies as well as suggest feasible solutions for the AI implementation gaps. Each phase plays a distinct role, from defining the key AI performance issues, followed by measuring the baseline metrics, then analysing the data for the identification of root causes, improving the process through targeted interventions, and finally controlling the outcomes with continuous monitoring and benchmarking mechanisms.

The DMAIC cycle is adopted in this study with the aim of providing a practical and structured assessment of how digitalisation levels impact AI effectiveness, while offering actionable insights for guiding AI integration within a mature digital ecosystem. As highlighted by Saad et al. (2024), DMAIC is proven to offer a highly adaptable and replicable framework structure that enables organisations to identify and address quality concerns, reduce process cycle time, enhance productivity, and improve operational efficiency. Moreover, the practical nature of the DMAIC cycle has led to the integration of several process improvement approaches (i.e., Green Six Sigma, Lean, Total Quality Management) to enhance its comprehensiveness in delivering operational excellence (Chiarini and Kumar, 2020). Each DMAIC phase will be explained to clarify the relationship between digitalisation and AI outcomes.

The define phase focuses on identifying key AI performance issues that stem from low levels of digitalisation or digital maturity within manufacturing environments. This diagnostic step involved reviewing operational reports, digital infrastructure readiness, and stakeholder feedback to uncover recurrent issues such as low AI prediction accuracy, fragmented or inconsistent data, limited access to real-time information, and weak integration between AI applications and legacy systems. Specific goals and objectives (i.e., enhancing AI prediction accuracy, improving data quality and consistency, improved integration across digital platforms) are formulated to guide subsequent improvement efforts. A precise problem definition and baseline metrics ensured focus and consistency throughout the DMAIC process. Next, the Measure phase focus on evaluating the impact of digitalisation levels on AI performance. Quantifiable performance indicators data such as AI prediction accuracy, real-time data availability, error rates, and process efficiency are collected. The data will then help to establish a performance baseline for identifying existing digital gaps and tracking progress toward improvement.

Figure 1: Six Sigma DMAIC cycle methodology for AI Implementation Gaps

The Analyse phase plays a central role in the DMAIC cycle by examining the root causes of AI performance limitations using the data obtained during the Measure phase. Root causes such as fragmented and unstructured data, absence of real-time data flow, disconnected IT systems, and limited integration across digital platforms ultimately lead to the constrained ability of AI technologies to learn from reliable data and generate actionable insights in real-time (Peretz-Andersson et al., 2024). Organisational factors (i.e., lack of individuals with digital knowledge and skills, resistance of stakeholders towards digital transformation) are also contribute to underperformance in AI implementation. The Improve phase focuses on designing and implementing digitalisation improvement solutions to address the root causes identified in the Analyse Phase. These strategies are designed with consideration of both technical and organisational factors, aiming to strengthen the organisation's digital infrastructure. Enhancing the digital ecosystem in this way allows AI systems to function with greater efficiency and effectiveness.

Lastly, the Control phase ensures long-term sustainability by fostering a culture of continuous improvement. It involves the establishment of continuous monitoring mechanisms such as real-time dashboards to track digital key performance indicators (KPIs) such as AI prediction accuracy as well as data availability and latency. Next, it also includes self-assessment tools to evaluate digital maturity improvement and periodic data audits to ensure data integrity. These practices enable organisations to track digitalisation progress and assess the ongoing performance of AI technologies. Another control mechanism is industry benchmarking, which enables organisations to compare their performance with that of their industry peers and adopt best practices to secure a competitive edge. Through consistent evaluation and adaptive governance, the Control phase supports the development of a mature digital ecosystem, positioning organisations to achieve scalable and reliable AI performance within Industry 4.0 manufacturing environments.

4. Case Analysis and Discussion

Table 1 presents the mapping of DMAIC phases that compile and synthesis data from three published studies across manufacturing industry, ranging from small and medium enterprise (SME) in general manufacturing by

Heilala et al. (2020), 3D printing processes by Rodriguez et al. (2022), to high-mix low-volume production environments by Peretz-Andersson et al. (2024). Despite differences in the operation process, the DMAIC results in Table 1 mainly focus on examining various challenges and improvement efforts related to AI implementation in manufacturing industry contexts. It follows the Six Sigma DMAIC cycle methodology to assess the relationship between digitalisation and AI performance as well as to illustrate the limitations of implementing AI without a mature digital ecosystem.

Table 1: DMAIC phases for selected studies of AI implementation in manufacturing industry

DMAIC Stage	Heilala et al. (2020)	Rodriguez et al. (2022)	Peretz-Andersson et al. (2024)
Define	Low digital maturity as key barrier to AI-based technologies adoption in manufacturing SMEs	Poor AI-based quality control and high defect rates in 3D printing manufacturing processes	Poor levels of digitalisation hinder manufacturing SMEs' capacity to apply effective AI solutions
Measure	Level of digitalisation in organisation (Enterprise Resource Planning (ERP), Big Data, AI applications)	Defect rates, Equipment efficiency, Digital computer-aided design (CAD) model data quality	Digital infrastructure readiness (ERP, cloud, IoT), Digital data quality, organisational AI capabilities
Analyse	Root causes include fragmented data, limited understanding of digitalisation and its opportunities, limited digital infrastructure	Root causes include poor digital connectivity, insufficient data volume for AI-model training, unreliable manual measurements	Root causes include weak data governance, resistance to digitalisation, limited AI system integration
Improve	Active IoT adaptation, cloud data systems, digital maturity assessments	Integrated IoT sensors, AI-model training optimisation, standardised measurement and quality parameters	Standardised cloud infrastructures, employee training, data platforms synchronisation with AI
Control	Continuous digitalisation level benchmarking, participation in industry digital ecosystem, self-assessment tools	Continuous digital CAD model data quality reviews, AI model performance (defect prediction accuracy), process KPIs	Continuous digital maturity benchmarking, cross-company AI reviews and knowledge sharing, data quality improvement

The case analysis results presented in Table 1 reinforce the argument that digitalisation must precede AI adoption. It reaffirms that digitalisation is not a complementary or optional step but a prerequisite for effective and sustainable AI implementation. All three studies in Table 1 demonstrate that low levels of digitalisation, characterised by inconsistent and fragmented data, poor system integration, and underdeveloped digital infrastructure in an organisation, can significantly constrain AI performance. For example, Heilala et al. (2020) highlight how the adoption of AI-based technologies in Finnish manufacturing SMEs was hindered by limited digital infrastructure and poor system integration, ultimately resulting in disconnected data systems as well as underutilisation of existing AI technologies. Next, Rodriguez et al. (2022) also demonstrate that even with AI-driven defect prediction technologies, the 3D printing defect rates remain high due to barriers such as insufficient digital connectivity, poor data quality from CAD models, and limited training datasets, all of which stem from a low level of digitalisation. Both examples emphasised that while AI technologies were introduced, their effectiveness is heavily dependent on the maturity of the digital ecosystem in the organisation. In contrast, organisations with higher levels of digitalisation are better equipped to support AI technologies in delivering accurate and reliable results. The relationship aligns with the broader goals of Industry 4.0 transformation, where digitalisation acts as the foundation that supports the smooth deployment of digital technologies such as IoT, big data analytics and intelligent automation. The consequences of overlooking an organisation's digital maturity include poor AI performance, inability to scale intelligent systems, and a failure to achieve competitive advantages (Kejriwal, 2023). Therefore, building a mature digital ecosystem is not merely beneficial but essential for leveraging AI's full potential across industries.

5. Conclusion - Prospect, recommendations, and future works

This study has demonstrated that digitalisation is a critical prerequisite for achieving effective and scalable AI implementation within the context of Industry 4.0. By applying the Six Sigma DMAIC methodology, the analysis of selected case studies highlights a consistent relationship between an organisation's level of digital maturity and the performance of its AI initiatives, particularly in the manufacturing industry. The higher an organisation's level of digitalisation, the more effectively and efficiently AI can operate, which leads to one step closer to realising a connected, intelligent production environment as envisioned by Industry 4.0. Manufacturers and investors should ensure that investments in AI are guided by a clear understanding of how AI initiatives align with the organisation's digital maturity and long-term transformation goals rather than simply following global trends. Meanwhile, policymakers should prioritise the ethical considerations of AI deployment within a mature digital ecosystem to mitigate the risks of data misuse and biased decision-making. Future work will focus on exploring quantitative models and collecting primary data through interviews or surveys to validate the impact of digitalisation on AI performance, as well as developing governance frameworks to ensure responsible and transparent AI deployment in the next stage of digital transformation.

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