How Does Enterprise Architecture Support Artificial Intelligence-Involved Digital Transformation in The Manufacturing Industry?

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Abstract

The adoption and impacts of enterprise architecture have long been a topic that has attracted researchers from a variety of fields. With the rise of Industry 4.0 and smart manufacturing, the integration of digital technologies like artificial intelligence (AI) has become the main direction for manufacturing companies to seize development opportunities. By reviewing eleven existing pieces of literature related to the role and functions of EA in digital transformation and AI-involved digital transformation's impact and complexity in manufacturing companies, this paper identifies the main challenges, such as managing vendor variety and additional technical requirements for AI implementation. Furthermore, multiple ways in which EA supports AI-involved digital transformation in the industry were discussed, including providing a generalised perspective to analyse various aspects of AI's influence, offering EA frameworks like DEA and ISAM to facilitate intelligent system management, guiding data management through data architecture, helping manage the combination of AI with other technology to enhance the overall capability. In the end, based on the review, the paper recommends manufacturing companies adopt The Open Group Architecture Framework® (TOGAF®) Architecture Development Method® (ADM) approach to develop and implement EA with a focus on the Business Architecture, Information System Architecture, and Technical Architecture phases, consider the AI implementation's implications for other components within the enterprise, and build an appropriate data architecture.

Keywords: Enterprise architecture (EA), digital transformation, Artificial intelligence (AI)

1. Introduction

With sweeping technology, Traditional Manufacturing enterprises have transformed into automated Smart Manufacturing gradually. Traditional Manufacturing lacks automation, in order to transit products or identify problems, human intervention is needed (Fanoro, 2022). There is no connection between machines, and humans are required to be in charge of machine operation. However, human-involved processes may still cause human error, which is less efficient. To mitigate this, Traditional Manufacturing started to transform its enterprise architecture (EA) more smartly. Smart Manufacturing is a decentralised production process, and machines can cooperate without humans (Fanoro, 2022). The benefits and enhancements that Smart Manufacturing brings are extraordinary. Phuyal et al. (2020) stated that when enterprises deployed Smart Manufacturing, their productivity surged by 17 - 20% due to enhanced machine utilization and resource maximisation.

Smart Manufacturing is able to rectify current or existing industrial problems, and a number of papers have pointed out its importance. However, only a few studies mention the path of rebuilding manufacturing enterprises from a traditional mindset to an automated one. Meanwhile, EA plays a pivotal role in facilitating manufacturing digital transformation.

Hence, the research question is raised: "How does Enterprise Architecture support Artificial Intelligence-involved digital transformation in the manufacturing industry?"

Accordingly, the remainder of this paper is structured as follows. The background provides fundamental information on digital transformation in the manufacturing industry and demonstrates three key terms in this paper: Digital Transformation, Artificial Intelligence, and EA， followed by a constructive literature review to summarise how manufacturing enterprises derive value from EA when AI takes part in it. After this, the paper discusses findings from literature reviews, including the benefits of AI, potential challenges, and functionality of EA supporting AI-involved transformation. Finally, recommendations and limitations are presented at the end of this paper.

2. Background

The manufacturing industry has a long and rich history which can be traced back to the industrial revolution during the 19th century. It is responsible for the fabrication of products from raw materials through machinery and chemical manufacturing processes, which changes the consumer market from handmade-dominated to man-and-machine or pure machine production. This industry makes mass production of goods and further mass manufacturing possible in most other industries. Efficiency in production is how manufacturing companies gain their competitive advantage and distinguish themselves from others. Therefore, continuous optimisation and improvement of production processes are very important for manufacturing companies. Digital transformation is the new trend in the manufacturing industry, which refers to integrating digital technologies and skills, such as Big Data, Robotics, and the Internet of Things (IoT), into different aspects of the manufacturing process. By embracing digital transformation, the manufacturing industry can improve its production efficiency and product quality and enhance flexibility.

3. Key Terms

3.1 Digital Transformation

Digital transformation is using digital technology to deeply change an enterprise in many aspects to improve its value creation and performance. The aspects could include systems, processes, business models, culture, management, policies, interrelationships between units, etc. (Westerman et al., 2011). As the development of various disruptive technologies such as IoT, machine learning, and AI is digitising or automating many key elements throughout the manufacturing process value chain, leading to optimisation, improved data utilisation, and productivity, the term Industry 4.0 arises, then it is important for manufacturing companies to invest in digital transformation to keep up with this trend for gaining competitive advantage (Ghobakhloo & Fathi, 2019).

3.2 Artificial intelligence (AI)

Artificial intelligence is a technology using computers to perform tasks simulating and extending human intelligence; its purpose includes learning, reasoning, perceiving, problem-solving, etc. (Arinez et al., 2020). AI is one of the most critical technologies for manufacturing in the era of Industry 4.0. It can process large amounts of data generated from the manufacturing process with high efficiency and accuracy, which humans could not achieve. This capability allows it to improve production line quality, efficiency, and sustainability, reduce labor hours and costs through detecting and categorising imperfections, optimising resource management, generating insights for guiding production, predicting equipment lifespan, and supporting robots to automate repetitive or dangerous tasks (Zeba et al., 2021).

3.3 Enterprise Architecture (EA)

Enterprise architecture is a structured and holistic framework articulating the various aspects of the organisation and how IT is integrated with business. It usually consists of a set of components defining business objectives and processes, data requirements, technology infrastructure, software applications, a current state architecture, a future state architecture, and a roadmap outlining the steps to change the enterprise IT (Jonkers et al., 2006). Therefore, EA can provide a comprehensive and unified understanding of the organisation, integrate the information silos to ensure that different units cooperate towards a common goal, and be a blueprint to guide the planning and management of IT in alignment with business strategy.

4. Literature Review

To answer the research question, there are eleven relevant papers identified in this section regarding different focuses on the intersection of AI, EA, and digital transformation.

Ilin et al. (2021) discusses the importance of the EA approach in addressing the complexity of organising the enterprise structure and managing IT and business automation while undergoing a digital transformation. The paper also briefly introduces how various industry 4.0 technologies could benefit companies in terms of flexibility, productivity, and decision-making, and how they could make changes in IT architecture and infrastructure. In particular, it uses an enterprise meta-model based on the EA approach to illustrate how AI is incorporated into a manufacturing company's EA (figure 1), how it impacts various architecture aspects, and how it supports the business process.

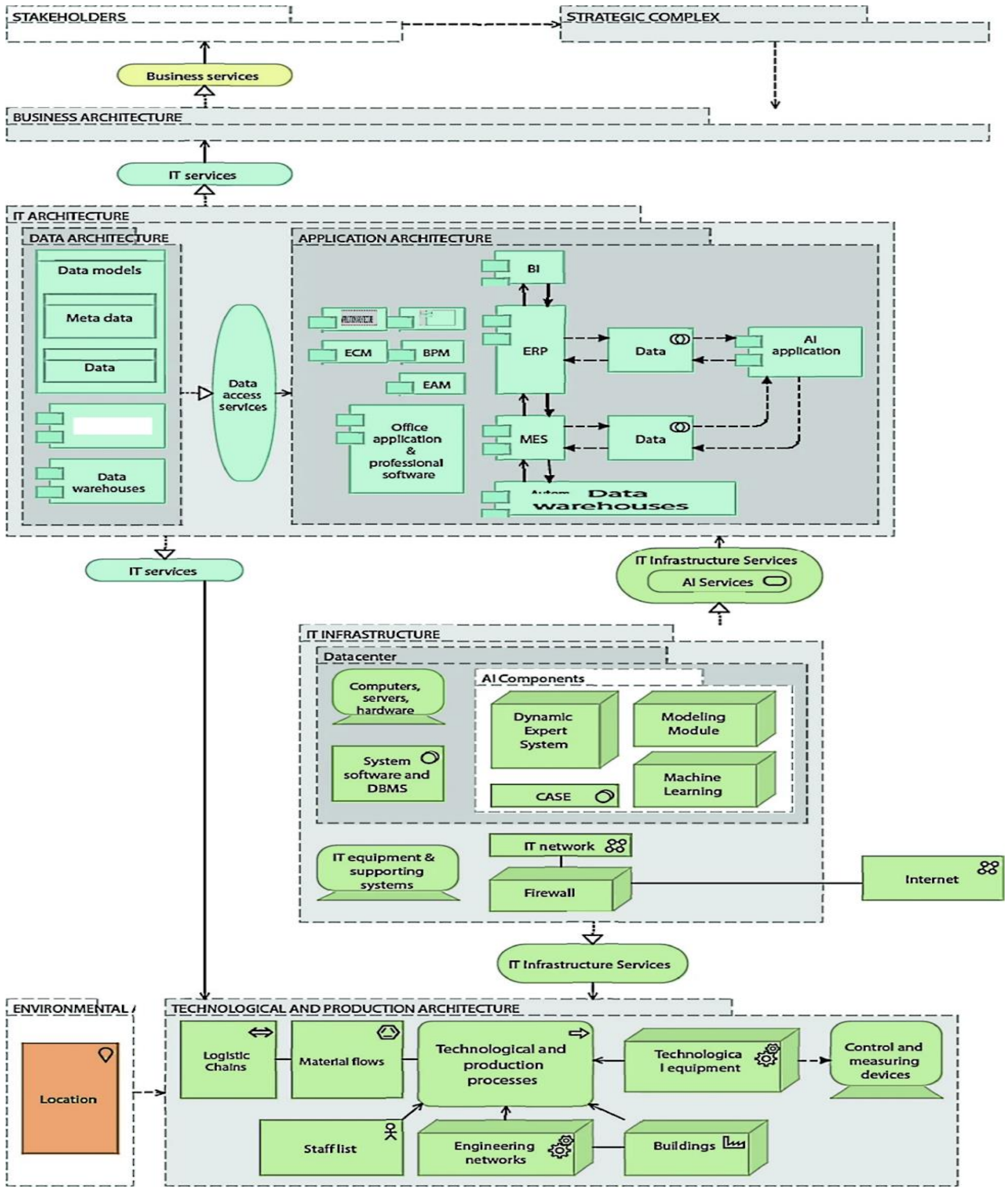

Figure 1: "AI representation in meta-model." (Ilin et al., 2021)

Zimmermann et al. (2020) investigate the key factors and models of a digital enterprise architecture that can facilitate the implementation of digital strategy. The successful establishment of intelligent digital systems (IDS) is defined in this paper as a strategic result of AI-based digital transformation initiatives. Accordingly, a Digital Enterprise Architecture as a relevant recommendation is proposed to ensure the alignment and effectiveness of structure regarding IDS (figure 2).

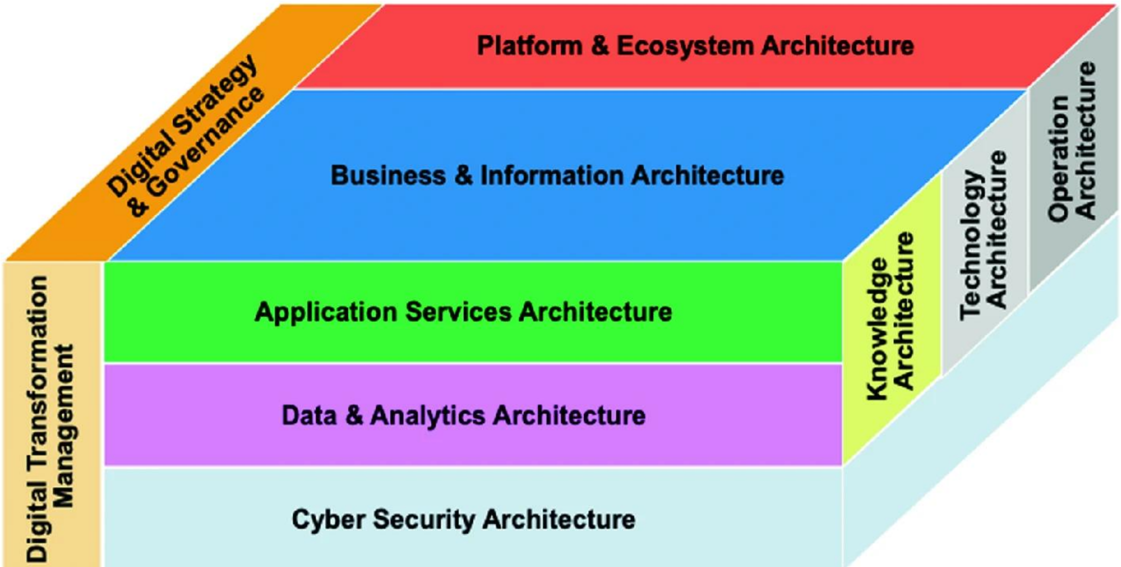

Figure 2: "Digital enterprise architecture reference cube" (Zimmermann et al., 2020)

According to Mo et al. (2023) and Podder et al. (2023), AI has the capability to improve the flexibility, responsiveness, robustness, and productivity of manufacturing systems. Mo et al. (2023) suggests an intelligent system architecture, a control system framework integrated with a hierarchically layered set of intelligent processing nodes (Albus, 1996), provides better manufacturing asset management and production control to flexibly change the behavior of the manufacturing system in order to satisfy the fluctuating customer and market demands. Podder et al. also mentions some areas in the manufacturing process which can improve the intelligent system architecture, such as handling complex data, automation, fault diagnosis and detection, and product improvement. Despite several benefits of AI, both papers suggest AI will not achieve desired results by implementing it singularly. It needs to be integrated with other advanced technologies. Mo et al. (2023) propose to adopt a digital twin, which is a virtual model designed to accurately reflect a physical object (IBM, 2022). Digital twin includes various sensors and data-collecting tools. The data collected will be relayed to a processing system and applied to AI. Podder et al. discuss a specific type of sensor, Micro-electromechanical systems (MEMS) sensors. MEMS sensors have the characteristics of miniaturisation, high accuracy, high quality, and performance at low cost due to the advancement in silicon chip manufacturing.

Trakadas et al. (2020) investigate how AI can be fully integrated into all parts of a manufacturing system through collaboration during digital transformation. They introduce the RAMI framework to create a common view and develop a shared understanding between all relevant participants. Based on RAMI, they design a new architectural approach to support digital transformation through addressing the current gap in the use of AI in the manufacturing industry. This service-oriented architecture consists of different layers and components, each serving a different function and purpose, such as Business, Functional, Information, and Communication Layers. A methodology for how to deploy this architecture is provided, along with an analysis of the potential industrial applications and their impact on the industry.

Alvarez-Coello et al. (2021) articulate a subset of EA-data architecture that has been analyzed with a data-centric approach in the car manufacturing industry. To achieve digital transformation, a shift in mindset and company-wide software architecture is pivotal and necessary. There are four transformation stages: (1) Siloed Data; (2) Pilot; (3) Data Hub; and (4) AI Factory. The paper suggests Principles of Modern Data Architecture (MDA) and a bottom-up approach (Data, Information, Knowledge, and Wisdom) enable enterprises to change from stage 1 (only one group can access data) to stage 4 (data becomes a shared asset) to address redundancy, improve automated processes, and achieve digital transformation.

In summary, Ing et al. (2020) discussed how the edge-cloud collaboration architecture empowers small and medium-sized enterprises (SMEs) with real-time decision-making and more automated manufacturing processes when there are resource constraints. The proposed architecture consists of four key components: (1) IoT-connected manufacturing equipment, (2) cyber-physical system, (3) intelligent edge, and (4) intelligent cloud. Intelligent Edge is more focused on integrating data with AI tools (e.g., deep learning) and transferring the collected data to intelligent cloud platforms to perform analysis. AI-driven analytics could assist SMEs in making smart decisions (i.e., more effective) and continuous improvement when interoperating with an enterprise's current manufacturing systems (e.g., CRM, QMS).

Kempegowda and Chaczko (2018) investigate how the EA approach and disruptive technology stack can complement each other, synergistically contributing to digital transformation in manufacturing. The application of AI is highlighted in this paper. Based on their literature review and experience in the industry, a major problem in terms of building a digital ecosystem in the manufacturing industry is identified as the complicated system network caused by the strategy-oriented procurement of ICT tools. The variety of vendors can challenge the integration of systems, inhibiting the effectiveness of digital transformation. To facilitate digital transformation, it suggests that TOGAF® can provide proven frameworks to balance the changing business needs and technology implementation. Enterprise can create architecture building blocks that are independent of a specific vendor and contribute to developing solution building blocks.

Zeid et al. (2019) argue that the successful implementation of interoperability in smart manufacturing can strengthen the efficiency of digital transformation by facilitating effective communication and error-prone data exchange between machines, systems, platforms, and users. However, based on their literature review, the traditional pyramidal hierarchy often inhibits interoperability between non-contiguous layers. To promote decision-making and decentralised operations in digital transformation, it is necessary to transform them into interoperable heterogeneous networks by using enterprise architecture. In the context of enhancing the interoperability of smart manufacturing, they discuss the characteristics of different architectures that could be used to support digital transformation. For example, RAMI is an architecture designed primarily for manufacturing applications, IIRA is designed for industries related to the Industrial IoT, and NIST is a service-oriented architecture specifically for smart manufacturing.

Hafsi & Assar (2016) explains the building blocks of digital transformation and the main challenges associated with it based on previous studies. It also aggregates the general benefits of using EA, including how EA acts as a foundation for executing strategic initiatives. Moreover, it shows how EA practice and its toolset adds value for enabling digital transformation in four different areas with the TOGAF® framework. Corresponding to the four focus areas of the Architecture Development Method® (ADM) approach, it explores EA's conducive effects in helping the entire enterprise have a common understanding of the target state, clarifying the architecture vision, distinguishing between diverse categories of architectural assets, identifying stakeholder's interest, stake and developing a communication strategy to gain support from them.

Correani et al. (2020) conduct a case analysis of three organisations in the manufacturing and service industry. Accordingly, an AI-involved digital strategy implementation framework is designed with ten elements, aiming to effectively assist the delivery of digital transformation projects by building a consistent connection between strategy development and implementation.

5. Discussions

In this section, the contribution of identified papers will be discussed in the context of our research question regarding the benefits of AI, challenges, and influence of EAs in supporting AI-related digital transformation.

5.1 Benefits of Adopting AI

These identified papers mention multiple benefits that AI-involved digital transformation could bring to the manufacturing enterprise, including:

- **Customisation**: AI can help manufacturers to better know the needs of customers by analysing customer data and preferences and customising products based on customers' needs.
- **Increased efficiency**: AI can give suggestions for production processes to reduce downtime and optimise resource allocation.
- **Monitor and manage quality**: AI can help manufacturers to monitor production lines, identify defects, and analyse root causes for improvements.
- **Automation**: AI allows automation equipment to perform more complex tasks and helps manufacturers to save labour costs.

Overall, it is fair to say that manufacturing industries can benefit from timesaving and process optimisation by incorporating AI into their architecture.

5.2 Challenges

Many challenges of digital transformation which need to be addressed by EA approaches can be identified. Kempegowda and Chaczko (2018) focused on the challenge of managing vendor variety while integrating multiple systems and technologies, where EA is required to provide a blueprint for the integration. Similarly, several articles mentioned the integration challenge regarding the complexity of planning and technical issues like interoperability between different systems or the need for additional technical capabilities and infrastructure while integrating AI. Besides these, many organisational and cultural level challenges were also identified, such as unclear roles, goals, and vision, resistance to change, poor business-IT communication, etc.

5.3 How EA can provide support

Each article can intersect with research question topics in different ways. Building on the interrelations among EA, AI, and digital transformation shown in these papers, six out of eleven papers can be considered as highly overlapping with the research question. First, Ilin et al. (2020) demonstrates that in the context of increasing needs for digital transformation, EA, as a recognised integration tool, provides a generalised perspective to consider and analyse the influence of AI techniques on various components of the organisation. By presenting how AI applications can be embedded in the manufacturing EA, the authors summarise that AI technology can be implemented with enterprise systems, contributing to production operations management.

Zimmermann et al. (2020), Mo et al. (2023), and Trakadas et al. (2020) confirm the significant role of AI in intelligent systems regarding digital transformation. The concept of intelligent digital systems (IDS) in digital transformation is mentioned in the literature, which describes a digital environment that combines hardware and software to provide intelligent manufacturing services. Zimmermann et al. (2020) and Mo et al. (2023) highlight the significance of AI techniques in constituting the IDS; accordingly, two different EA frameworks — DEA and ISAM — are respectively proposed to support digital transformation. DEA integrates extended architectural services components from bottom to up (Zimmermann et al., 2020). It highlights that EA should be service-oriented and loosely coupled to adapt to the dynamic digital ecosystem, and the use of AI can enable agile architectural management. Similarly, the ISAM proposed by Mo et al. (2023) intends to provide a framework for developing standards and performance measures for intelligent manufacturing systems. It consists of a hierarchically layered set of intelligent processing nodes (including sensors, analysis tools, task-performing tools, etc.) in manufacturing. These nodes are organised as a control system for smart decision-making, planning, analysis, and reporting activity. Considering the complex and dynamic intelligent digital systems in the context of digital transformation, it is necessary to involve different layers in EA to facilitate management. Meanwhile, EA can support AI-involved digital transformation by providing a management framework to collaborate with AI applications and systems. This is echoed by Trakadas et al. (2020) in the context of manufacturing IoT. It extends the RAMI 4.0 model by embedding AI into the processes. This framework facilitates the collaboration among human and AI-based virtual entities within a manufacturing site, thus increasing the AI integration from different parts of manufacturing systems.

To facilitate manufacturing enterprises transforming digitally, a suitable Data Architecture is proposed by Alvarez-Coello et al. (2021). Four digital transformation stages have been introduced; the initial stage is named Siloed Data (i.e., data is not treated as shared assets), and the final stage is AI Factory (i.e., enterprises develop a standard for AI enabled transformation). More specifically, Modern Data Architecture in this paper indicates how data will be collected, governed, and engaged with AI applications. To further optimise the effectiveness of digital transformation from a data perspective, Ing et al. (2020) suggest an edge-cloud collaboration architecture by combining and managing the AI project with cloud features to enhance the functions of data calculating, sharing, and storing. Building on the management assistance of EA frameworks, this combination of AI and other technology infrastructures can be a reference for a more integrated and deeper application of AI digital transformation.

In terms of the manufacturing industry, the remaining literature also reflects the research question topic by considering EA's impact on digital transformation and the effective implementation of AI strategy for digital transformation. Kempegowda and Chaczko (2018), Zeid et al. (2019), Ilin et al. (2020), and Hafsi and Assar (2016) discuss the relationship between general EA approaches and digitalisation. Among them, Zeid et al. (2019) emphasises the importance of ensuring interoperability in the EA structure. The rest mention the contributions of TOGAF® to offer proven frameworks and methodologies for enterprises. To build the connection between EA strategy planning and strategy implementation for successful digitalisation, Correani et al. (2020) propose an implementation framework to bridge the gap, starting from scope establishment and ending with customer consideration. AI applications can be used to optimise the manufacturing process (Podder et al., 2023). Building blocks for AI applications in manufacturing operations are also included in the framework.

This section has reviewed how EA can support AI-involved digital transformation from eleven papers, identifying the benefits of EA and AI in digital transformation projects. Multiple models of EA are suggested to guide digital transformation and enhance AI functionality and integration, such as data architecture, ISAM, RAMI4.0, etc. Notably, the implementation of various frameworks can be divided into two phases: architecture design and implementation, which combine to contribute to a successful digital transformation. EA strategy formulation in this context should consider the different focuses for various phases and perspectives. The literature shows that the EA frameworks mentioned in the selected papers can be properly identified and fit in the right position in the TOGAF® ADM®, such as reference model, business, IS, and technical architectures. Accordingly, TOGAF® could be used as guidance for the EA design and implementation.

5.4 Other important factors

Besides the above discussion, there are other factors that are critical for facilitating EA to support digital transformation.

- **Consider beyond individual AI implementation**: AI applications and implementations are powerful; however, AI implementations have limitations when used in industrial settings (Podder et al., 2023). When performing the transformation, all relative factors need to be considered comprehensively rather than relying on AI tools completely.
- **EA building blocks**: Building blocks refer to various technologies, such as Cloud Computing and Big Data Analytics. As Kempegowda and Chaczko (2018) stated, Architecture Building Blocks (ABB) could meet business requirements by not binding with particular products or services. In other words, ABB assists enterprises in choosing the most appropriate block to form solutions and accomplish digital transformation.
- **Interoperability between humans and machines**: Humans can control machines through intuitive actions (Ke et al., 2018). That indicates successful interoperability empowers enterprises to improve efficiency, eliminate redundancy and manage transformation with high proficiency.
- **Business-IT Alignment**: To achieve transformation, enterprises need to ensure consistency between the Business unit and IT unit. According to Ing et al. (2020), when integrating Edge-Cloud Collaboration Architecture with the current quality management system, enterprises need to ensure alignment.

6. Recommendation

6.1 Adopt TOGAF® ADM® to guide EA development

Based on the previous discussion, TOGAF® ADM® is well suited for EA development and implementation of AI-related smart manufacturing. The process of building EA requires continuous validation checks against the initial expectation to ensure that EA evolves in line with the company's expectations and best practices (Josey, 2011). Accordingly, eight generic phases in the TOGAF® ADM® can provide practical guidance for architectural development (figure 3). After establishing a clear vision, it is recommended to first focus on phases B (Business Architecture), C (Information System Architecture), and D (Technical Architecture phase) to realise architecture delivery. During this process, the reference models can offer a common framework for the different types of technical, IS, and business components (Timm et al., 2015). Due to the open nature of TOGAF®, industries are also advised to reconfigure or modify the reference model according to their differentiated environment and individualised process characteristics. Corresponding to the previous challenge of lacking interoperability, the use of uniform and compatible components and interfaces can contribute to an interoperable architecture, increasing the integration between humans and machines (Setiawan & Yulianto, 2018). This can further strengthen the functional fit of the EA to the company and facilitate AI-related digital transformation.

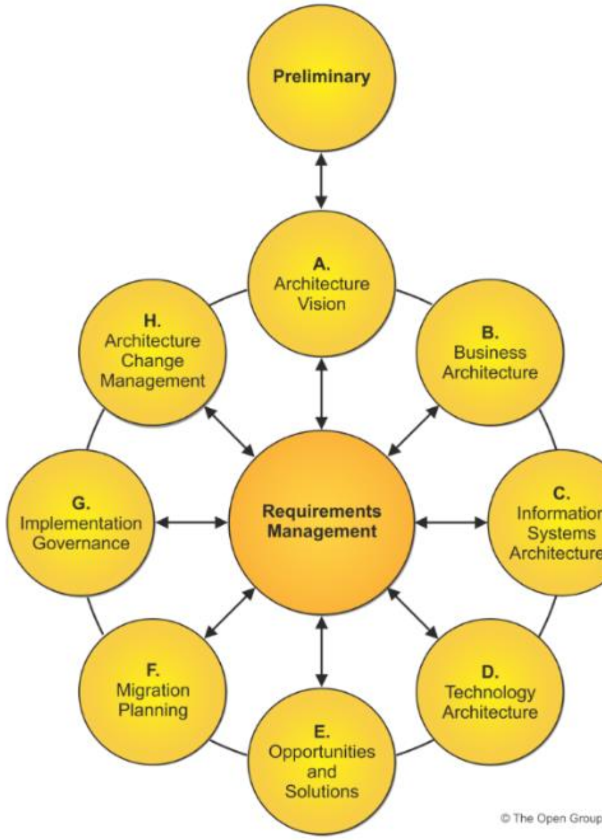

Figure 3: TOGAF® ADM® (The Open Group, n.d.)

6.2 Consider the potential combination and implications while integrating AI

Given the understanding that AI applications need to be implemented with other techniques to achieve the desired results, the use of AI should be considered in a broader context. For example, the paper mentioned before presents an AI-involved edge cloud-based architecture. This can be considered as a combination of AI and cloud computing technologies, integrating and uploading data on the cloud platforms for further desired intelligent analysis. Another instance is embedding AI-driven analytics into enterprise systems to facilitate data calculation and automation for the manufacturing industries. Generally, using AI with other components can better achieve the intended outcome than deploying AI applications individually.

Notably, when AI is combined with other processes, the potential impact on the industry EA environment should be considered. Regular tests and evaluations can assist in adapting AI-involved algorithms or other components of the architecture to business needs. To avoid unwanted disruption, it is suggested to follow the previously recommended TOGAF® ADM® practices, developing the target architecture description before making any impulsive changes.

6.3 Build a suitable Data Architecture

As analysed previously, one of the major uses for AI applications in the manufacturing industry is data processing. A proper data architecture is suggested, providing standards and guidelines for data management. There are several principles or guidelines to lead enterprises; for instance, do not process data within a single scope (e.g., only in business scope) that will limit data reusability and impede digital transformation. Based on the fundamental principles of Modern Data Architecture (Alvarez-Coello et al., 2021), enterprises could define a clear data handling process that improves data reusability, data security, and data quality.

7. Limitation

There are some limitations of this analysis report, including:

- The referenced literature for this report is limited to the documents in the reference list.
- Segmentation in the manufacturing industry. This report is only focused on the overall manufacturing industry on a macro scale.
- Bias might exist in this report as the literature selected could contain authors' biases, preferences, or interests.
- There are time constraints for data and referenced literature. Some older or newer materials may not have been included in the report.

8. Conclusion

In conclusion, this literature review demonstrates the importance of Enterprise Architecture in the realm of digital transformation. Building on the analysis of key terms, this study extracts relevant information from the eleven reviewed papers to answer the research question: How does Enterprise Architecture support Artificial Intelligence-involved digital transformation in the manufacturing industry? The primary benefits of AI adoption are identified as customisation, efficiency, quality assurance, and automation, and the key challenges, such as managing vendor variety and additional technical requirements to set up AI, are covered in the discussion. Accordingly, this research recommends TOGAF® as guidelines and principles for Enterprise Architecture configuration to highlight its importance in facilitating digital transformation, especially when AI-enabled technologies participate. Meanwhile, the importance of building an appropriate data architecture and the impact of AI involvement on the surrounding environment is suggested to be considered.

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