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Business Process Architecture for the Integration of Artificial Intelligence at Aerospace Organizations

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Artificial Intelligence (AI) is proliferating, and companies are working to integrate this powerful capability into their workplaces (McLaren, 2023). Some AI technologies are designed to be narrowly focused, performing specific tasks, while others focus on providing more general solutions. Software companies like Microsoft are working to integrate AI into their operating systems and business applications. Microsoft has recently introduced its Copilot® (Copilot), an "Everyday AI companion" (Mehdi, 2023, p. 1). Software like Copilot will allow users to interface with their computer workstation more naturally and conversationally.

AI is fast becoming an exciting new computer revolution that allows one to automate workplace tasks like never before. Companies in the aerospace industry must adapt their business process architecture to take advantage of this revolution; they must understand how to best implement AI technologies like Copilot to create a competitive advantage. The current study conducts a literature review to identify current and potential AI applications beneficial to the aerospace industry. It utilizes the findings to model a new business process architecture for integrating AI in the workplace.

Background

Organizations across many industries, including the aerospace industry, have realized the need for digital transformation, which has been ongoing since the dawn of modern computer systems but has more recently risen out of the movement toward the fourth industrial revolution known as Industry 4.0 (Akter et al., 2022; Golov & Myl'nik, 2022; Kretschmer & Khashabi, 2020). The primary focus of Industry 4.0 is the connectivity of industrial equipment and processes with business systems. Digital transformation offers improved operational performance, financial performance, and competitive advantage (Vial, 2019).

Digital transformation intends to implement several enabling technologies in all areas of business operations, including customer engagement, design, manufacture, and supply chain management (Akter et al., 2022; Van Nguyen et al., 2023). These enabling technologies include automation, digital twin, cloud computing, and AI (Van Nguyen et al., 2023). Industry 4.0 digital transformation is particularly synergistic with AI technology as the digital connectivity of industrial equipment and business processes resulting from digital transformation provides the big data input that AI can efficiently analyze (Peres, 2020).

The aerospace industry is in the process of adopting and implementing Industry 4.0 digital transformation concepts. Though they are still in the early phases of this effort, the potential benefits of this transformation continue to grow as the technology involved continues to improve at an ever more rapid pace (Hickie & Hickie, 2021). More specifically, recent rapid advances in AI, such as natural language processing, have created new potential that few aerospace organizations have yet to implement. These advanced tools are also well suited for implementation in regions with advanced economies as they rely more on high technology than low-skilled labor (Hickie & Hickie, 2021).

Statement of the Problem

There are numerous studies on the application of AI in the aerospace industry, but these studies are focused on narrow application of AI for use in performing specific tasks. Although the potential benefits of AI can be profound, there are challenges and costs to this implementation, and if not implemented properly, the costs can outweigh the benefits (Plathottam et al., 2023). The current study intends to summarize the existing literature and identify any common aspects between the various applications that can be combined to form a unifying architecture for the implementation of AI more holistically in the aerospace industry.

Significance

The value of the current study is significant as the use of AI in the aerospace industry can improve efficiencies and provide a competitive advantage, particularly in predictive maintenance, quality assurance, and process optimization (Plathottam et al., 2023). The timeliness of the study is also significant because the aerospace industry is still early in implementing AI in Industry 4.0 digital transformation efforts (Plathottam et al., 2023). By understanding the various applications for AI, their implementation will be more successful, and identifying common aspects of AI applications will allow a more unified architecture for the implementation of AI in the aerospace industry.

Research Questions

The following research questions are proposed:

RQ1: Can common aspects of AI applications be identified to develop a unified architecture for implementation in the aerospace industry?

HN1: Common aspects of AI applications cannot be identified to develop a unified architecture for implementation in the aerospace industry.

HA1: Common aspects of AI applications can be identified to develop a unified architecture for implementation in the aerospace industry.

Literature Review

A review of the relevant literature is presented below, focusing on applications of AI that are suitable for the aerospace industry. The literature review has been conducted inductively, seeking facts and practical analytical methods related to the research subject to formulate conclusions based on logical analysis of the findings. As the literature findings have accumulated, they have been categorized as shown by the headings.

Business Administration

A study by Mihai et al. (2023) examined how technologies such as AI influenced the European Union's (EU) digital intensity index and found that the most common implementation of AI included speech recognition, robotic automation, and autonomous mobility. The study also found that organizations were most interested in implementing AI for management and recruitment decisions. However, utilizing AI for business administration and enterprise management was found to be lacking and considered an area requiring additional research and investment.

Establishing a performance evaluation framework for the AI system is essential when implementing AI for business administration (Gudigantala et al., 2023). Gudigantala et al. found that firms without such a framework fail to derive value from AI. The key to establishing an AI performance evaluation framework is using performance measures that align with the business strategy and value creation outcome. Gudigantala et al. referred to these framework components as objectives and key results (OKRs) and key performance indicators (KPIs). The business objectives are transformed into questions the AI system can take as input. The KPIs are used to evaluate the outcome of AI decisions in terms of the business performance in achieving its objectives.

Dumas (2023) described the integration of AI and business process management systems (BPMS) to form augmented-AI business process management systems (ABPMS). An ABPMS differs from a BPMS in that a BPMS is designed to manage processes according to fixed algorithms. In contrast, ABPMS can interact with employees of an organization to modify and improve processes according to employee input and in response to KPIs. An ABPMS can engage employees in conversation via natural language processing either as part of a business process or if a situation arises outside of preset limits associated with a business process. Such limits can be set to enable transparency and trust between humans and AI. An example of these limits might be the operating temperature of a specific manufacturing process. Within established limits, the AI can adapt and compensate for the process, but beyond the specified limit, the AI is to notify a human. The AI can interact with the human at a conversation level to find root causes for out-of-limit situations, the AI can make process change recommendations, and the human can approve these changes.

Decision Making

Project ASSISTANT is an AI technology in development intended to improve decision-making in manufacturing and production environments through machine learning (ML) and digital twin technology. Project ASSISTANT will optimize manufacturing and production system design decisions, operations efficiency, and production schedule (Castañé et al., 2023). A study by Keding and Meissner (2021) determined that management tends toward over-acceptance of AI decision-making in a research and development investment context. The perception that AI produces a better decision can lead to lax efforts to validate the results of the AI analysis, which can be compounded by the fact that AI analysis is not generally well understood and not always transparent. Keding and Meissner recommend that management utilizing AI-augmented decision-making be trained in AI ‘fusion skills’, enabling their role in the judgment of AI decision-making outcomes.

According to Schmitt (2023), there are still gaps in the capability of AI to provide business decisions compared to the relatively high capability of AI to perform analytical prediction. Schmitt reviewed the performance of AutoML, a type of ML that does not require experts to prepare the data set used to train the AI. Schmitt found that AutoML does not quite meet the same level of accuracy in prediction as manually trained ML; however, the speed and cost savings may make up for this lack of accuracy in many cases. The potential for AutoML to improve in accuracy and its ease of implementation will likely contribute to the widespread use of AI for decision-making at organizations of all sizes. Additionally, Schmitt noted that using AI for augmented decision-making in coordination with human decision-makers would be particularly useful as the capability of AI in this area goes through its early growth stages.

Requirements Development

The analysis of customer feedback through AI has been demonstrated by Henriksson and Zdravkovic (2022), who extended the capability of an AI metamodel to the analysis of natural language user reviews. The metamodel scanned user reviews and identified positive and negative feedback regarding video game user experience, bug reports, and feature recommendations. The AI metamodel analyzed these natural language reviews, generated statistics, and recommended requirements for future upgrades.

Technical Design

Design iteration and the costs associated with prototype development and testing can be minimized by utilizing generative AI in the product design phase (Bilgram & Laarmann, 2023; Plathottam et al., 2023). Generative design AI receives system requirements as an input and outputs a range of optimized design solutions. Human designers can select from the output designs or further refine the requirements. As requirements change, updated designs can be rapidly generated by the AI. Chatbots using large language models and natural language processing, such as ChatGPT, have shown that conversational interaction via text prompts can be used to iterate design options to produce digital prototypes at a quality level on par with entry-level experts. These draft-quality prototypes can provide an expert with a quick starting point for further prototype refinement (Bilgram & Laarmann, 2023).

Dong et al. (2021) reviewed several deep learning (DL) AI models applicable to aircraft design and describe the potential opportunities and challenges of implementation. DL AI performed better than traditional pure physics and mathematical-based computational fluid dynamics (CFD) analysis. The performance of DL is better at aerodynamic CFD analysis in the transonic region, where nonlinearities are seen due to shock wave interaction (Sabater et al., 2022).

Trade studies in design are necessarily linked to cost, and cost estimating is a critical component of the proposal phase for any development program. A study by Van Nguyen et al. (2023) reviewed the potential for AI-enabled cost estimating in the aerospace industry. The study found that using AI-enabled cost estimating improved by 80% in prediction accuracy and allowed for greater execution speed and flexibility. The AI system was integrated with Internet data related to material costs, allowing real-time adaptation to market changes.

Manufacturing

Augmented reality (AR) is useful in manufacturing environments, and AI-driven AR is particularly beneficial (Sahu et al., 2021). Utilizing AI for reaction to environment illumination, depth perception, real-time augmentation, closed-loop registration (alignment of virtual and non-virtual objects), image rendering, and other AR-related computational functions shows promise for increasing AR performance and usefulness in the manufacturing environment. These AI-driven AR improvements will facilitate more rapid growth in the use of AR technology in the aerospace manufacturing industry.

Integration of AI with manufacturing processes such as production planning, production control, and quality control has shown potential for improving performance, particularly when combined with the concept of an AI-enabled digital twin (Huang et al., 2021). A digital twin is a virtual representation of a physical product intended to mirror the as-built configuration. The digital twin often includes postproduction updates based on the service life history of the product. In the production phase of the product life cycle, AI can be utilized to simulate outcomes of manufacturing processes, predict the effect of machine wear on product surface finish, and predict the effect of temperature gradient on product mechanical properties. AI can be utilized to optimize the next step in production based on the data captured in the digital twin if the digital twin is updated after each manufacturing step with the as-built condition data.

Vast amounts of data need to be collected to feed the ML and DL AI algorithms to realize AI's benefits in manufacturing. Data comes from many sources and formats within the manufacturing environment. A review of the industrial application of AI conducted by Peres et al. (2020) found that standards in data collection are needed to allow for common solutions to be developed that different organizations can utilize. To enable this standardization of data collection, the concept of FAIR (findable, accessible, interoperable, and reusable) should be incorporated along with strong cybersecurity measures.

Methodology

This study used an integrative literature review to identify the applicable studies related to the integration of AI at an organization, particularly an aircraft design and manufacturing organization (Snyder, 2019). An integrative literature review examines and synthesizes the existing literature to develop a new framework. Analysis of the literature using the integrative approach relies on logic and conceptual reasoning rather than quantified data analysis (Torraco, 2005). Business process categories have been selected to facilitate the analysis by logically grouping the relevant literature; these categories are listed in Figure 1. The primary contribution of the relevant literature was then summarized, and elements observed in the contributions were identified and noted for inclusion in the new high-level business process architecture model. This method allows for a logical process in determining whether the existing literature can provide a basis for forming the new business process architecture for implementing AI.

Figure 1

Business Process Categories

Business Administration

Decision Making

Requirements Development

Technical Design

Manufacturing

Results

An analysis of relevant literature has been conducted using an integrative approach, as described in the methodology section. The relevant literature has been categorized according to business processes applicable to an aerospace organization, the contribution of the relevant literature has been summarized, and elements identified for inclusion in the new business process architecture have been extracted from the literature contribution summaries. The results of the literature review analysis are shown in Table 1. Once captured, the elements identified from the literature review were used to modify a baseline business process architecture.

Table 1
Literature Categorization

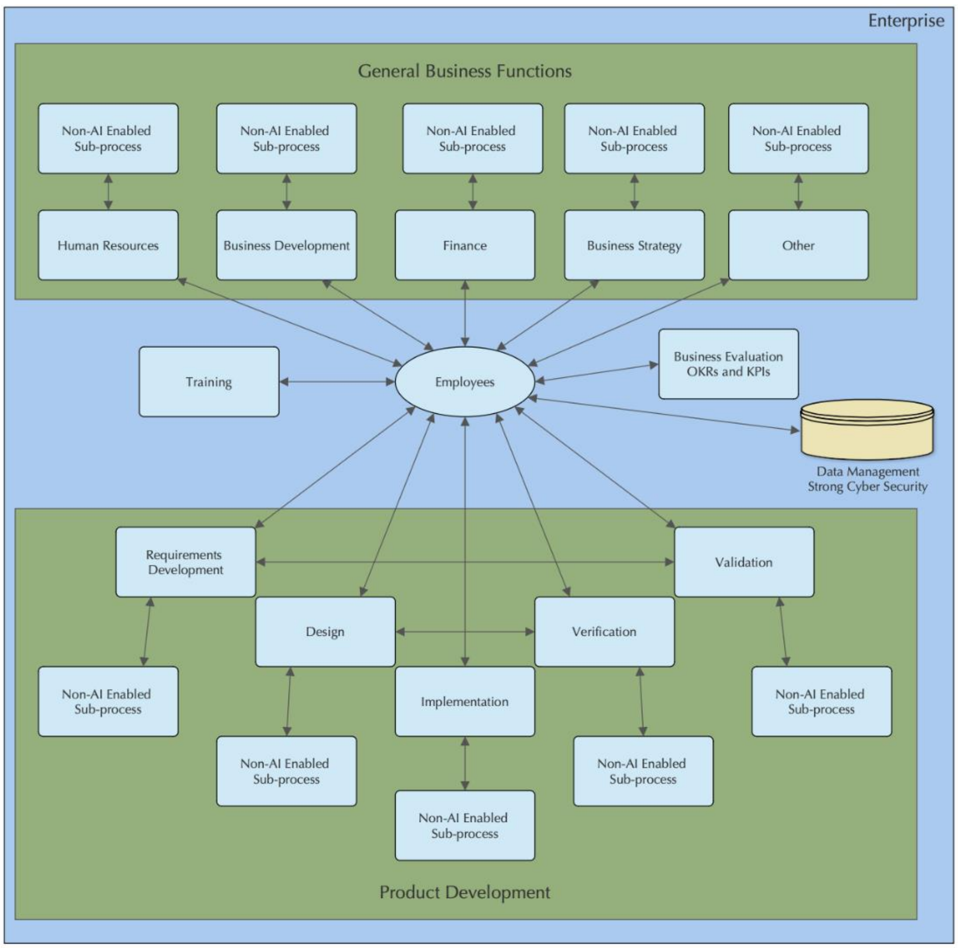
Author	Category	Contribution	Captured Elements
(Mihai et al., 2023)	Business Administration	Common AI implementation includes speech recognition, robotic automation, and autonomous mobility; utilization of AI for business administration and enterprise management requires additional research and investment.	
(Gudigantala et al., 2023)	Business Administration	AI performance can be evaluated using OKRs and KPIs.	Feedback loop to evaluate both business and AI performance
(Dumas, 2023)	Business Administration	ABPMS can be used to manage business processes.	ABPMS to manage business processes
(Castañé et al., 2023)	Decision Making	Project ASSISTANT is an AI technology in development intended to improve decision-making in manufacturing and production environments.	AI-enabled subprocess
(Keding & Meissner, 2021)	Decision Making	Management utilizing AI-augmented decision-making needs to be trained in	AI fusion skill training of employees.

Author	Category	Contribution	Captured Elements
		AI ‘fusion skills’, enabling their role in the judgment of AI decision-making outcomes to prevent over acceptance of AI decision outcomes.	
(Schmitt, 2023)	Decision Making	AutoML can potentially speed up AI training; however, it currently lacks manual training in prediction accuracy. Augmented AI is the best near-term solution.	AutoML to facilitate ABPMS
(Henriksson & Zdravkovic, 2022)	Requirements Development	AI is capable of translating user input and feedback into product requirements.	AI-enabled subprocess
(Plathottam et al., 2023)	Technical Design	Generative AI can be used to iterate digital design prototypes quickly.	AI-enabled subprocess
(Bilgram & Laarmann, 2023)	Technical Design	Chat-based AI can be utilized to facilitate generative AI in design iteration.	Conversive user interface
(Dong et al., 2021)	Technical Design	AI shows potential to outperform traditional CFD design calculations.	AI-enabled subprocess

Author	Category	Contribution	Captured Elements
(Sabater et al., 2022)	Technical Design	AI shows potential to outperform traditional aerodynamic design calculations, particularly in the transonic region.	AI-enabled subprocess
(Van Nguyen et al., 2023)	Technical Design	AI shows the potential to outperform traditional cost-estimating processes and enables real-time adaptation to market data.	AI-enabled subprocess
(Sahu et al., 2021)	Manufacturing	AI has the potential to enhance AR capability and performance, which in turn can enhance manufacturing processes.	AI-enabled subprocess
(Huang et al., 2021)	Manufacturing	AI can improve manufacturing processes' performance, particularly when combined with the digital twin concept.	AI-enabled subprocess
(Peres et al., 2020)	Manufacturing	Data management should employ the FAIR concept and strong cybersecurity to enable AI's benefits in manufacturing.	FAIR data management

The initial high-level baseline architecture model was formulated to be typical of an aerospace design and manufacturing organization and is shown in Figure 2. This baseline business process model consists of general functional business processes and product development processes. The product development processes are depicted as a vee product development model (Liu, 2016). The baseline model also includes data management and employee training and has the organization's employees as the central hub for interaction with the business processes. Employees are responsible for evaluating the business performance according to OKRs and KPIs.

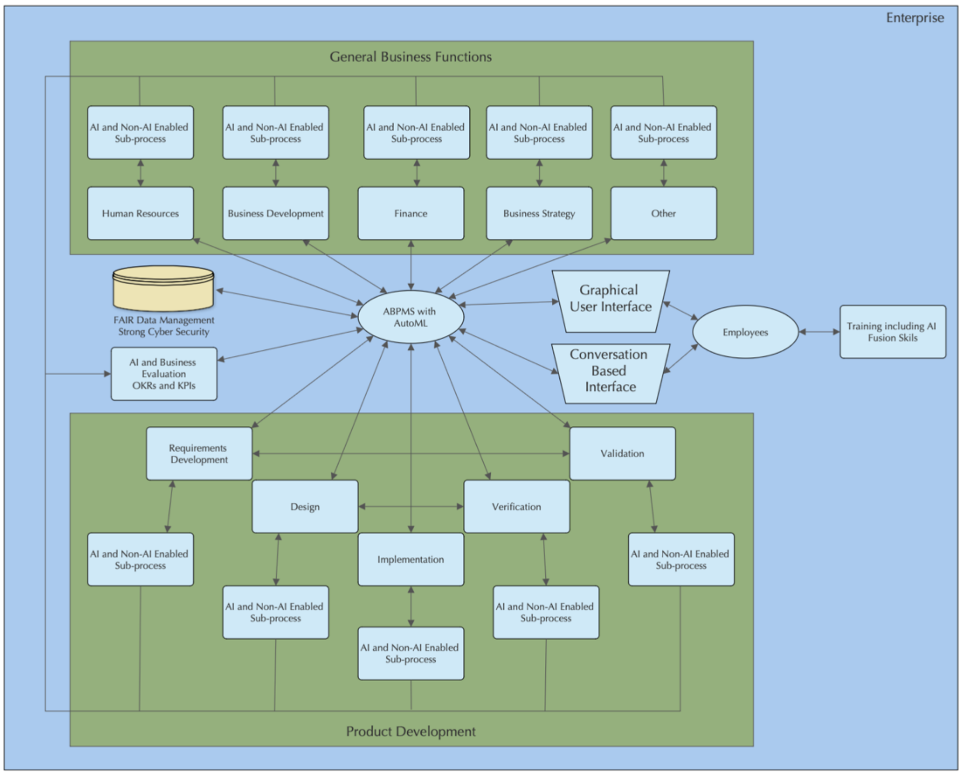
Figure 2
Baseline Business Process Model



The high-level architecture model resulting from the literature analysis and AI integration into the business processes is shown in Figure 3. The new model augments the organization's employees with an AI composed of an ABPMS facilitated by AutoML capability. This realignment places the AI as the central hub of interaction with the business processes and moves the employees to the periphery, interacting with the business processes via the AI. Interaction between the employees and the AI uses conversation or a web-based graphical user interface. Employee training is replaced with training that includes AI fusion skills, and data management is enhanced with the FAIR concept. In addition to the central ABPMS, AI is incorporated at the subprocess level. At this process level, specific tasks are automated using AI in cases where AI outperforms traditional process automation or quantitative analysis. Finally, the business and AI evaluation are combined in a feedback loop.

Figure 3

AI-Enabled Business Process Model



Discussion

An integrative literature review analysis was conducted to develop a new high-level business process architecture; a model of this architecture is shown in Figure 3. The new architecture aims to enable the digital transformation of aerospace organizations by integrating AI into the business process. The literature review shows that advances in AI capability are reaching the level where such an architecture is feasible. Currently, AI is utilized in the aerospace industry in a limited fashion at the subprocess level. This limited utilization primarily focuses on using AI to perform specific tasks, such as improved computations, which are not integrated with other AI-enabled tasks. The new architecture incorporates AI at the sub-process level and the central hub of the process structure. In the baseline business process architecture, the employees were located at the central hub of the process structure. Placing AI as a central hub provides a layer of intelligent automation between the organization's employees and business processes. The new architecture allows AI to manage the business process via an ABPMS, which can improve efficiencies due to the speed of automation. It will allow human employees to focus on the highest-level decisions while AI provides feedback on business performance and recommended process improvements. The new architecture can shorten product development times by providing a means for rapid digital prototyping and real-time adaptation to requirement changes.

An example implementation of the new architecture might resemble the following scenario: Employees will ask the AI to perform time-consuming tasks such as design trade studies or generate design iterations outputting computer-aided design models. The AI will perform the tasks according to the business processes and sub-processes to achieve the desired output. Sub-processes may involve the AI utilizing traditional software applications or separate AI-enabled software to complete tasks. Company proprietary data will be combined with publicly available data from the Internet to allow the AI to train using AutoML. The AI will then evaluate the output compared to the organization's OKRs and KPIs and recommend process improvements for the human employees to review. Human employees will be trained in AI fusion skills for better human-AI collaboration.

Conclusion

A study was conducted to develop a new architecture for integrating AI at aerospace organizations. The study used an integrative literature review to logically analyze AI's current and potential applications beneficial to the aerospace industry. The literature review identified AI-related elements to develop a new AI-enabled business process architectural model.

The research question, "Can common aspects of AI applications be identified to develop a unified architecture for implementation in the aerospace industry?" has been answered in the affirmative, and the common elements captured from the literature review are shown in Table 1. As such, the null hypothesis, HN1, "Common aspects of AI applications cannot be identified to develop a unified architecture for implementation in the aerospace industry." has been rejected.

Future research is recommended to perform a pilot study to evaluate the performance of the new AI-enabled business process architecture. Such a pilot study would first require assembling the necessary information technology infrastructure, including AI capabilities. The pilot study could investigate the potential for using the natural language processing capabilities of Copilot or ChatGPT to interface between employees and the ABPMS. Additionally, a data set sufficient to provide initial training of the AI system will be required. The use of AutoML will speed up the training process, and the scale of the pilot study should be sufficiently sized to assess the architecture's performance while minimizing the required resources.

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