AIMS5.0 AI Toolbox: Enabling Efficient Knowledge Sharing for Industrial AI

Gergely Hollósi[‡], Dániel Ficzere[‡&], Attila Frankó[‡&], Máté Bancsics[‡],
Ruba AlMahasneh[‡], Csaba Lukovszki[‡], Pál Varga[‡]

[‡]*Dept. of Telecommunications and Artificial Intelligence*, *Faculty of Electrical Engineering and Informatics*
Budapest University of Technology and Economics, Megyetem rkp. 3., H-1111 Budapest, Hungary
[&]*IIoT Division, AITIA International Inc.*, 48-50 Czetz J. Str. H-1039 Budapest, Hungary
corr.: hollosi.gergely@vik.bme.hu

***Abstract*—Industry 5.0 continues to reshape the industrial processes, the pivotal role of AI services in optimizing operations has become increasingly evident. Although the state-of-the-art AI models are widely employed across diverse application areas, the industrial sector faces numerous challenges in navigating through a plethora of the available AI models and libraries.**

Indeed, lacking effective employment guidelines for AI models can hinder their utility and decrease their adaption. This paper introduces the AIMS5.0 AI Toolbox, an innovative framework designed to address this challenge by fostering industrial knowledge sharing and distribution. The AIMS5.0 AI Toolbox serves as a comprehensive resource for industrial practitioners. It offers an integrated holistic platform for sharing models, tools, best practices, and guidance specifically directed towards the industrial AI-based consumers. Through its multifaceted approach, the toolbox facilitates seamless exchange of insights and expertise among the industrial actors. In addition, the AIMS5.0 AI Toolbox gives new ways to the process of fast prototyping by leveraging well-established AI-based models and libraries. By incorporating solid best practices and recommendations, the toolbox provides a structured framework for industrial users to harness the power of AI effectively.

***Index Terms*—AI, machine learning, artificial intelligence, Arrowhead, industrial AI, edge AI, industrial automation, SOA, intelligent services**

I. Introduction

In the constantly evolving landscape of industrial processes, the integration of Artificial Intelligence (AI) has emerged as a transformer force, reshaping the way industries operate, optimize, and innovate. AI, with its capacity for sophisticated data analysis, real-time decision-making, and adaptive learning, emerges as a catalyst for increased efficiency, precision, shorter time to market and fast adaptation of innovative ideas.

In this competitive environment, AI emerges as a promising toolset offering solutions beyond traditional automation processes. By exploiting opportunities provided by machine learning algorithms, neural networks, and advanced analytics, AI empowers industrial processes to exceed routine automation, facilitating continual learning, adaptation, and performance optimization in various sectors, including manufacturing, supply chain management, energy production or even logistics. The application of AI in industrial processes is underscored by the prospect of predictive analytics, preventive maintenance, and decision-making in different areas of the industry. To overcome the ever-evolving requirements and new innovative approaches, a broad knowledge of AI algorithms and technologies are inevitably essential for implementation and deployment.

In the dynamic field of industrial applications, the establishment of a dedicated toolbox to store AI tools as functional modules is of increased significance. The AIMS5.0 AI Toolbox, presented in this paper, serves as a comprehensive approach, fostering the seamless sharing of innovative solutions, experiences and best practices tailored to address challenges to industry. By assembling a comprehensive collection of AI tools, industries can facilitate the collaborative dissemination of expertise, allowing developers to draw upon shared experiences and proven methodologies in solving innovative, and even complex problems. This toolbox promotes the culture of knowledge-sharing, accelerating the exchange of insights and approaches to simplify industrial operations.

II. Related work

Over recent years of intensive development, there has been a substantial effort leading to the identification of both the main characteristics and challenges inherent in industrial processes. The identified use cases covers various areas of manufacturing, supply-chain management, maintenance, operation and resource management, as well. Regarding these issues, there are several researches and surveys which are covering the role of AI in industrial domains.

AI's integration in the industry has significantly impacted how businesses interact with clients, partners, and manage supply chains [1], [2], [3].In the literature, AI researches are focusing on inventory management [4], [5], customer feedback [6], [7], [8] and customization [9], [10]. Moreover, leveraging AI- powered solutions has led to enhanced customer experiences, streamlined collaborations with partners, and optimized supply chain operations, ultimately driving overall business success.

Design process [11], [12], planning, and manufacturing processes [13], [14], [15] , are considered prominent industrial segments that utilize AI in a new innovative and efficient era. From concept ideation to production optimization [16], AI-powered solutions are reshaping how industries approach product development, planning, and manufacturing, resulting in an improved design quality, streamlined operations, and enhanced productivity. Within the manufacturing sector, AI-driven robotics and automation [17], [18] systems are optimizing production lines, enhancing the end-product quality with AI-supported quality assurance[19], [20] and process monitoring [21], [22], [23].

Furthermore, AI's integration in maintenance, operation, and recycling processes has revolutionized how industries manage their assets, optimize operations, and promote sustainability.

It is apparent that AI-powered solutions are transforming the way businesses approach asset management, whether that was in predictive maintenance [24], [25], [26] or in the life-cycle management itself [27], [28]. They reduce the production downtime, and the waste contamination [29], [30]. A relevant survey machine learning applied for smart maintenance and quality control is provided by [31].

The goal addressed in this paper is not unique; sharing AI solutions for specific problems has been increasingly emphasized in recent times, operating at various levels. Established development frameworks, including TensorFlow, PyTorch, Azure ML, Watson ML, and OpenVINO, seamlessly integrate solutions to address challenges in industrial such as quality control, predictive maintenance, process or supply chain optimization, control systems or anomaly detection. Moreover, encouraging knowledge sharing has led to the growth of various platforms, such as AI Hub, GitHub, the AI Marketplace by NVIDIA, and the AWS Marketplace for ML, as well as Intel AI Builder, or other open source AI Toolboxes as the HuggingFace, Haystack or LangChain. Although these solutions exist AIMS 5.0 AI Toolbox is able to complement their ability catalyzing the fast and efficient sharing of AI solutions, experiences and best-practices.

III. Toolbox concept

While there are a number of AI tools and toolboxes available, industrial applications pose new challenges against design and development. The goal of the AIMS 5.0 AI Toolbox is not to replace the existing toolboxes but to extend the existing solutions to provide common platform for information and knowledge exchange for industrial AI applications. More precisely, AIMS 5.0 AI Toolbox will guide and supervise the design and development process in a more harmonized and structured approach, and thus,maximize the usability of AI models on a larger industrial scale. [32].

To support AI service design and implementation, the AIMS 5.0 AI Toolbox has some well-defined objectives, as follows:

Decrease the time-to-market By providing design templates and samples, reusable and compatible tools, the time-to-market can be decreased by fast prototyping.

Reliability and security Describing best practices helps the designers to enhance reliability.

Prompt evaluation To test industrial proof-of-concepts, the toolbox provides tools which can be easily evaluated.

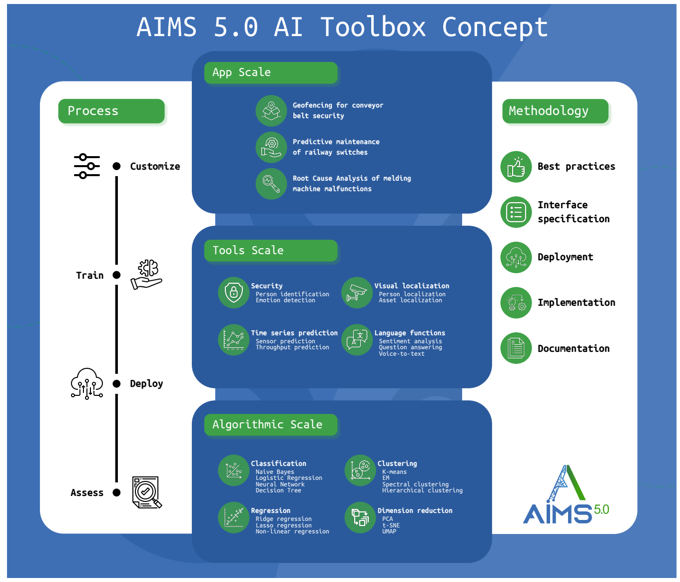

Fig. 1. AIMS 5.0 AI Toolbox concept with different AI service scale levels supported by a common process and methodology. The examples in the different scales are for illustrative purposes only; there are many other categories and examples. (source: [32])

Composition The AI Toolbox collects tools which can co-operate with each other through standard interfaces in order to be composed to implement complex applications. Composition helps to achieve better re-usability of AI tools.

Share knowledge The toolbox provides means to exchange and share valuable knowledge and best practices.

Extensive support The AIMS 5.0 AI Toolbox supports natively any existing AI tools and toolboxes.

A. AI Toolbox scale levels

Figure 1 shows the main concept of the AIMS 5.0 AI Toolbox. There are four levels of AI Service scale, differing primarily in granularity. The three *implementation* based levels are supported by the fourth – mostly *theoretic* – methodology scale. In the following, the four levels are presented more deeply and compared to the objectives and requirements.

1) Application scale: Application scale is the highest scale level of AI services, where the AI services provide solutions for complete use cases, e.g., a whole predictive maintenance service specifically for railway switches. The aim of the AIMS 5.0 AI Toolbox is to reach application scale by composition of reusable and composable tools.

2) Tools scale: Tools scale is a compromise between algorithmic scale and application scale. Tools basically provide applied AI methods, which are commonly one or more AI models combined with some inner logic to solve a recurring problem. E.g. localization of assets in a factory consists of a couple of small steps, but the problem arises in numerous use cases. Tools scale can provide excellent reusable scale and support rapid development. Also, careful design of service interfaces can provide good composability.

3) Algorithmic scale: The level of Algorithmic scale is granular since well-known AI and ML algorithms are implemented as AI services. Algorithmic scale is mostly about choosing the best service interfaces to provide composable services. However, using pure algorithms – while being highly reusable – requires great effort to implement complex use cases. Also, using pure AI algorithms requires great knowledge of AI methods and techniques, which is against rapid development.

4) Methodology scale: Being on a theoretical scale, the methodology provides specifications, requirements, and best practices for implementing AI services. However, while the Methodology scale can also be considered an independent level of AI service scales, it is best to imagine it as the basis of all other service scale levels since it can provide means to fulfill all the objectives and requirements of AI Toolbox services. Consequently a feasible methodology should be provided at all scale levels to provide integrated and unified interfaces to facilitate adaptation to heterogeneous environment and to satisfy composability criteria while implementing AI services.

Although this hierarchical approach still holds (from practical aspect) a flat toolbox concept is recommended. As it is shown in [32] the most promising implementation scale is the tool scale. While providing tools for AI application implementation requires a limited knowledge on basic AI methods, a feasible service interface could be designed to satisfy composability criterion.

B. AI Toolbox life-cycle

The life-cycle of AI services shares the very same four steps (see Figure 1). To provide re-usable services, the *customization* step makes it possible to tailor the service to special needs. This includes e.g. setting of the parameters. The next step is optional, however, most algorithms are required *training* to perform specific tasks, e.g., detecting uncommon objects in an image. Training can be complex and shall support widely spread frameworks to efficiently accomplish fine-tuned models. *Deployment* is a crucial point in the life-cycle, since models require variable resources or perhaps massive parallelization. In addition, standard solutions for deployment, containerization and extendability to industrial systems (e.g. the Arrowhead Framework) are common requirements.

IV. AI TOOLBOX DESIGN

The previous section introduced the main objectives and motivations of the AI Toolbox. This section presents the fundamental requirements for the AI Toolbox, examining how these ideas can be implemented and outlining the broad architectural framework that should characterize the AI Toolbox. Figure 2 presents the high-level architecture, including the building blocks of the tools and the AI Toolbox Support. Contributors to the toolbox are responsible for supplying tools, and their role includes providing ready-to-test notebooks along with necessary supplementary information and files, incorporating best practices related to the topic and the actual implementation. The notebook format is particularly advantageous for supporting proof-of-concept development, offering essential tools for interactive development. Additionally, the AI Toolbox Support role involves consolidating these notebooks into a Tool catalogue and Application Wiki, while also providing the necessary support and libraries for the tool deployment.

A. AI Toolbox Support building blocks and implementation

Arguably, one of the key goals of the AI Toolbox is to minimize time-to-market, emphasizing the swift and uncomplicated deployment of proof-of-concept applications and tools. Simplicity entails the availability of pre-existing example tools that can be readily employed, either as-is or with minor adjustments. We have defined 4 building blocks that will form the AI Toolbox Support:

Catalogue Applications consist of tools chained together. Catalogue contains the list of available tools already included in the AI Toolbox and their usage, categorized by field of application.

Deployment tools Prompt evaluation of AI Tools requires actions to seamlessly deploy tools as services. The primary method for deploying these notebooks as services involves containerized services a well-defined interface. However, this can be expanded to include various deployment scenarios for cutting-edge industrial frameworks, such as Arrowhead. For the deployment of implemented tools as services, the AI Toolbox requires deployment tools that utilize the deployment configuration specified by the tools.

Toolbox libraries An essential requirement to align with the philosophy of the AI Toolbox is the ability to deploy these notebooks across various architectures without the need for code rewriting. These libraries handles the interface compatibility and management for the tools, as the responsibility for handling interface integration lies with the AI Toolbox.

Application Wiki AI Toolbox users require a comprehensive guide on its usage. This Wiki encompasses all essential information on implementing specific applications through integrated tools, offering insights into best practices and guidelines for contributing to the AI Toolbox.

To underpin this entire concept, a flexible and open-source Integrated Development Environment (IDE) is crucial. This IDE should have the capability to run notebooks, even in remote settings. Moreover, there are instances where deploying large AI models locally may not be feasible, or multiple notebook instances may need to utilize the same model, making remote running essential. These requirements serve as the foundation for operating and developing AI-based tools and industrial applications. Additionally, version control emerges as another indispensable requirement for the AI Toolbox, for which the well-proven solutions (e.g. Git, Subversion, Mercurial, etc.) are employed.

B. Tool building blocks

In this section, we outline the five fundamental building blocks that form the core components of the tools. These elements represent what we believe a collaborator should

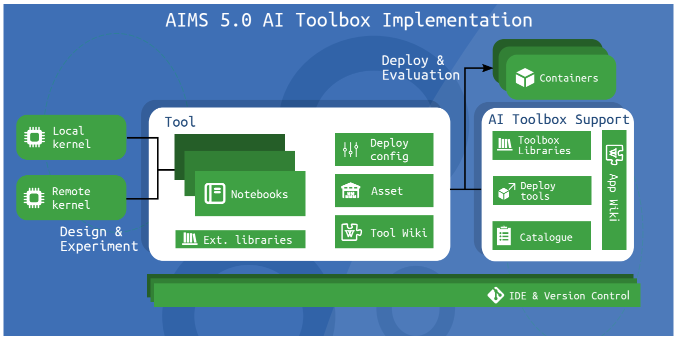

Fig. 2. AI Toolbox high level implementation design

incorporate into the tools to contribute to the AI Toolbox, as detailed below:

Notebooks The AI Toolbox builds around the concept to use notebook-based tool implementations from the contributors. The notebook format is in line with the proof-of-concept applications as they provide excellent framework to test new ideas fast. If the notebook meets certain requirements, they can be deployed immediately.

Deployment configuration In order to deploy the notebooks as services the tools should provide the necessary parameters for as a form of deployment configurations according to the Application Wiki description.

External libraries These libraries are necessary for implementing your solutions, and they come pre-written by other developers. However, bare reference to external libraries is also sufficient.

Asset These contains any external data sources which are necessary for a certain tool, i.e. images for an object detection tool or a text document for a context injection tool.

Tool Wiki This is the most important building block of a tool, a Wiki page containing the best practices about and experiences about the tool and the application where this tool can be used.

C. The flow of contribution

The process for contributing to the AI Toolbox is illustrated in Figure 3. When ready to contribute, the first path diverges for individuals with an application or tool intended for integration into the AI Toolbox. In the case of an application, it needs to be broken down into separate tools that can be integrated into the AI Toolbox. Subsequently, a check of the AI Toolbox catalogue is necessary to determine whether there is an existing tool with a similar solution, as the contribution steps may vary accordingly. As previously mentioned, the Application Wiki provides details on the essential building blocks (depicted in Figure 2) required for a tool to be integrated into the AI Toolbox. If all building blocks are in place, one can proceed to integrate the tool into the AI Toolbox. This involves both the integration of the tool itself and the modification of the Application Wiki to reflect the tool's applicability. Moreover, contribution doesn't necessarily entail introducing an entirely new tool; existing ones can be modified or extended with minor changes, such as code, assets (data sources), or additional best practices outlined in the Tool Wiki.

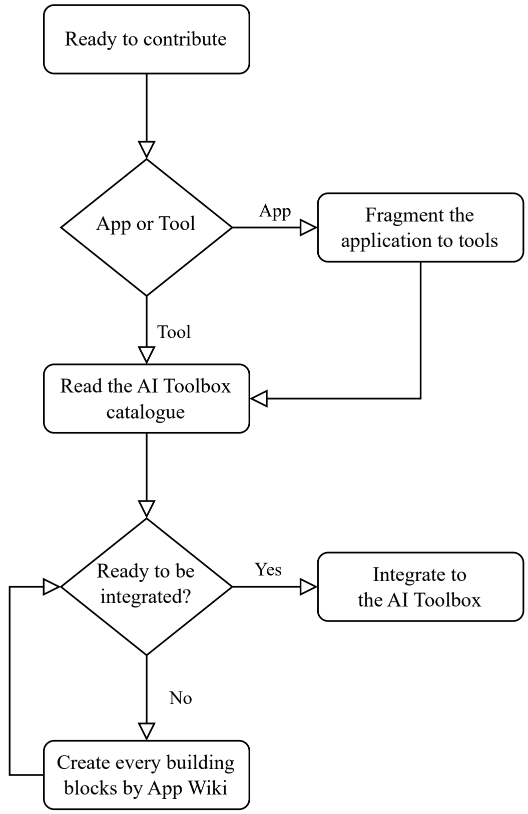

Fig. 3. The flow of contribution to the AI Toolbox

V. Tool Integration Example

To illustrate the conceptual framework of the AI Toolbox and its constituent building blocks, we present a use case involving a Question and Answering (Q&A) Large Language Model (LLM) with domain-specific context. Two tools have been created: an LLM tool for Q&A and another for obtaining a specific context related to our question, using a method known as Context Injection or Retrieval-Augmented Generation, which is widely recognized in the current landscape. The user can ask a question from the context injection tool, and based on the provided context, the LLM can respond to domain-specific questions via REST API.

In this section, we aim to introduce the development and deployment process of these two AI-related tools, highlighting the connection to the AI Toolbox, and explaining how individuals can contribute to the AI Toolbox after developing these tools. The implementation architecture of these tools is depicted in Figure 4. Before contributing to the AI Toolbox, it is essential to check the Tool catalogue to see if there are already similar tools in the AI Toolbox.

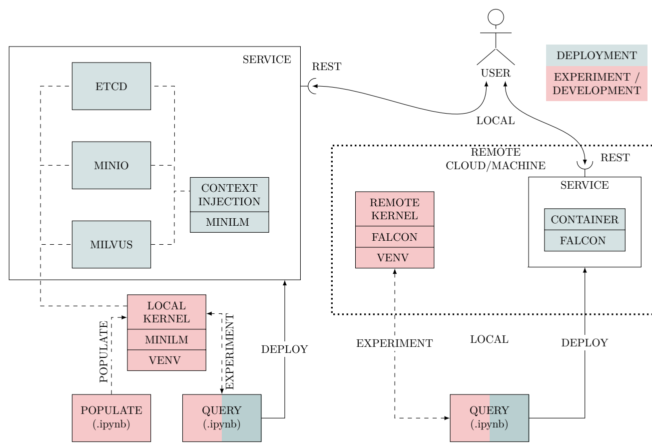

Fig. 4. The implementation of the LLM-based Q&A example

A. Integration of an LLM tool

Several AI applications, including Large Language Models (LLMs), often demand substantial resources, making it practical to deploy these services on remote machines. For the purpose of our demonstration, we have chosen the Falcon 7B open-source LLM model. The model has been deployed on a remote machine, operating on a remote kernel within its dedicated virtual environment. Suppose our experimentation with the model is complete, and the notebook is finished. To use Falcon as a service and integrate it into the AI Toolbox, the following elements need to be created in accordance with the requirements of the tool building blocks:

Notebooks The notebook must be formatted according to the specifications outlined in the Application Wiki. It should consist of two parts: a setup section managing the model parameters and a service section configuring the inputs, outputs, and deployment mode of the service. In our example, the default mode is to deploy these services in Docker containers and communicate with them via REST API.

Deployment configuration It involves creating the necessary files for Docker containers – the Dockerfile for building images and the docker-compose file for running these images.

External libraries The essential external libraries should be specified along with the Dockerfile.

Asset In the case of our LLM tool, no asset files are required.

Tool Wiki The final crucial building block is to construct the Tool Wiki for LLMs in general, providing information on what they are, how to fine-tune them, and best practices for the specific LLM model Falcon.

With all these building blocks in place, the system is ready for deployment and integration into the AI Toolbox. Upon integration, it is essential to update the tool catalogue, and simultaneously, the Application Wiki must be modified to delineate the purposes for which your LLM tool can be employed based on your experience.

B. Integration of a context injection tool

The development process for the context injection tool follows a structure similar to the LLM tool, but we want to emphasize the distinctions. Context injection for smaller datasets may not be as resource-intensive, allowing it to be executed locally. In the general context injection process for a text document, it involves several steps: first, the document needs to be divided into chunks, then these chunks are embedded into a high-dimensional space, stored in a vector database, and finally, semantic search is performed to extract context. However, we won't delve into the specifics of how these tasks are accomplished, as they can be intricate, particularly for swift operations. Moreover, the intricate details are beyond the scope of this discussion. The content of the context injection tool's building blocks are as follows:

Notebooks The crucial point to note here is that additional notebooks, beyond the query.ipynb, may exist, as seen in this scenario where additional notebooks are employed to populate the vector database. Our solution and requirements are not confined to a single notebook for tool implementation; multiple notebooks can contribute to the overall tool functionality. The formatting requirements for the query.ipynb are akin to the previous case.

Deployment configuration Another distinction is that, in this instance, the deployed service comprises four Docker containers: one for context injection (utilizing minilm for embedding) and the other three responsible for creating the vector database (milvus database). The challenge lies in the complexity of the docker-compose file, as it needs to encompass the configuration of four Docker containers and their interrelationships.

External libraries Similarly, they have to be defined along with the Dockerfile.

Asset In the context injection process, external data (assets), such as a domain-specific text document, is required to obtain the context.

Tool Wiki This should encompass best practices regarding context injection, detailing how to split the document into chunks, perform high-dimensional embedding, populate the vector database, select metrics for semantic search, and other relevant considerations.

After the development and experimenting phases are completed, the tools are prepared for integration into the AI Toolbox. The Tool catalog and Application Wiki can then be updated and expanded accordingly.

VI. Conclusion

The evolving landscape of Industry 5.0 necessitates a keen focus on optimizing industrial operations through advanced AI services. Our paper has addressed the challenge faced by the industrial sector in navigating the vast array of AI models and libraries without clear guidelines for their efficient use and deployment. We introduced the AI Toolbox as an innovative framework to overcome this challenge by fostering knowledge sharing and distribution within the industrial community. We presented the primary objectives and requirements of the AI Toolbox, along with the overarching design architecture, the contribution flow for contributors, and ultimately showcased the integration of two specific tools. The demonstration focused on illustrating how a tool could be integrated, using a Q&A LLM application as a concrete example.

The AIMS5.0 AI Toolbox aims to be a comprehensive resource, serving industrial practitioners with a platform for sharing models, tools, best practices, and guidance tailored to AI applications in industrial settings. Further, the AI Toolbox accelerates the development process of proof-of-concept solutions. By incorporating solid best practices and recommendations, the AI Toolbox provides a structured framework for industrial users to harness the power of AI effectively.

ACKNOWLEDGMENT

The research leading to these results is funded by the EU Chips-JU organization under grant agreement 101112089, within the project AIMS5.0 and from the partners' national programs and funding authorities. Part of this work is created within the Arrowhead fPVN project, supported by the Chips-JU and its members, as well as by national funding authorities from involved countries under grant agreement no. 101111977.

REFERENCES

[1] R. Toorajipour, V. Sohrabpour, A. Nazarpour, P. Oghazi, and M. Fischl. Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research*, 122:502–517, 2021.

[2] M. Pournader, H. Ghaderi, A. Hassanzadegan, and B. Fahimnia. Artificial intelligence applications in supply chain management. *International Journal of Production Economics*, 241:108250, 2021.

[3] S. Modgil, S. Gupta, R. Stekelorum, and I. Laguir. Ai technologies and their impact on supply chain resilience during covid-19. *International Journal of Physical Distribution & Logistics Management*, 52(2):130–149, 2021.

[4] T. Sustrova. A suitable artificial intelligence model for inventory level optimization. *Trends Economics and Management*, 10(25):48–55, 2016.

[5] D. Preil and M. Krapp. Artificial intelligence-based inventory management: a monte carlo tree search approach. *Annals of Operations Research*, pages 1–25, 2022.

[6] A. Adak, B. Pradhan, and N. Shukla. Sentiment analysis of customer reviews of food delivery services using deep learning and explainable artificial intelligence: Systematic review. *Foods*, 11(10), 2022.

[7] R. Perez-Vega, V. Kaartemo, C. R. Lages, N. Borghei Razavi, and J. Männistö. Reshaping the contexts of online customer engagement behavior via artificial intelligence: A conceptual framework. *Journal of Business Research*, 129:902–910, 2021.

[8] P. S. Lee, I. Chakraborty, and S. Banerjee. Artificial intelligence applications to customer feedback research: A review. *Artificial Intelligence in Marketing*, pages 169–190, 2023.

[9] J. Wan, X. Li, H.-N. Dai, A. Kusiak, M. Martínez-García, and D. Li. Artificial-intelligence-driven customized manufacturing factory: Key technologies, applications, and challenges. *Proceedings of the IEEE*, 109(4):377–398, 2021.

[10] J. Wan, X. Li, H.-N. Dai, A. Kusiak, M. Martinez-Garcia, and D. Li. Artificial-intelligence-driven customized manufacturing factory: key technologies, applications, and challenges. *Proceedings of the IEEE*, 109(4):377–398, 2020.

[11] R. Verganti, L. Vendraminelli, and M. Iansiti. Innovation and design in the age of artificial intelligence. *Journal of Product Innovation Management*, 37(3):212–227, 2020.

[12] M. Ghoreishi and A. Happonen. Key enablers for deploying artificial intelligence for circular economy embracing sustainable product design: Three case studies. In *AIP conference proceedings*, volume 2233. AIP Publishing, 2020.

[13] T. Yang, X. Yi, S. Lu, K. H. Johansson, and T. Chai. Intelligent manufacturing for the process industry driven by industrial artificial intelligence. *Engineering*, 7(9):1224–1230, 2021.

[14] S. Fahle, C. Prinz, and B. Kuhlenkötter. Systematic review on machine learning (ml) methods for manufacturing processes identifying artificial intelligence (ai) methods for field application. *Procedia CIRP*, 93:413–418, 2020. 53rd CIRP Conference on Manufacturing Systems 2020.

[15] J. F. Arinez, Q. Chang, R. X. Gao, C. Xu, and J. Zhang. Artificial Intelligence in Advanced Manufacturing: Current Status and Future Outlook. *Journal of Manufacturing Science and Engineering*, 142(11):110804, 08 2020.

[16] A. N. Bakhtiyari, Z. Wang, L. Wang, and H. Zheng. A review on applications of artificial intelligence in modeling and optimization of laser beam machining. *Optics & Laser Technology*, 135:106721, 2021.

[17] S. S. Shekhar. Artificial intelligence in automation. *Artificial Intelligence*, 3085(06):14–17, 2019.

[18] F. T. Tschang and E. Almirall. Artificial intelligence as augmenting automation: Implications for employment. *Academy of Management Perspectives*, 35(4):642–659, 2021.

[19] L. Vandewinckele, M. Claessens, A. Dinkla, C. Brouwer, W. Crijns, D. Verellen, and W. van Elmpt. Overview of artificial intelligence-based applications in radiotherapy: Recommendations for implementation and quality assurance. *Radiotherapy and Oncology*, 153:55–66, 2020. Physics Special Issue: ESTRO Physics Research Workshops on Science in Development.

[20] G. Mahadevaiah, P. Rv, I. Bermejo, D. Jaffray, A. Dekker, and L. Wee. Artificial intelligence-based clinical decision support in modern medical physics: selection, acceptance, commissioning, and quality assurance. *Medical physics*, 47(5):e228–e235, 2020.

[21] V. Pandiyan, S. Shevchik, K. Wasmer, S. Castagne, and T. Tjahjowidodo. Modelling and monitoring of abrasive finishing processes using artificial intelligence techniques: A review. *Journal of Manufacturing Processes*, 57:114–135, 2020.

[22] A. L. Alfeo, M. G. Cimino, G. Manco, E. Ritacco, and G. Vaglini. Using an autoencoder in the design of an anomaly detector for smart manufacturing. *Pattern Recognition Letters*, 136:272–278, 2020.

[23] B. Lindemann, B. Maschler, N. Sahlab, and M. Weyrich. A survey on anomaly detection for technical systems using lstm networks. *Computers in Industry*, 131:103498, 2021.

[24] W. J. Lee, H. Wu, H. Yun, H. Kim, M. B. Jun, and J. W. Sutherland. Predictive maintenance of machine tool systems using artificial intelligence techniques applied to machine condition data. *Procedia CIRP*, 80:506–511, 2019. 26th CIRP Conference on Life Cycle Engineering (LCE) Purdue University, West Lafayette, IN, USA May 7-9, 2019.

[25] T. Zonta, C. A. da Costa, R. da Rosa Righi, M. J. de Lima, E. S. da Trindade, and G. P. Li. Predictive maintenance in the industry 4.0: A systematic literature review. *Computers & Industrial Engineering*, 150:106889, 2020.

[26] D. Cardoso and L. Ferreira. Application of predictive maintenance concepts using artificial intelligence tools. *Applied Sciences*, 11(1), 2021.

[27] L. Wang, Z. Liu, A. Liu, and F. Tao. Artificial intelligence in product lifecycle management. *The International Journal of Advanced Manufacturing Technology*, 114:771–796, 2021.

[28] A. Kaab, M. Sharifi, H. Mobli, A. Nabavi-Pelesaraei, and K. wing Chau. Combined life cycle assessment and artificial intelligence for prediction of output energy and environmental impacts of sugarcane production. *Science of The Total Environment*, 664:1005–1019, 2019.

[29] L. Andeobu, S. Wibowo, and S. Grandhi. Artificial intelligence applications for sustainable solid waste management practices in australia: A systematic review. *Science of The Total Environment*, 834:155389, 2022.

[30] K. H. Yu, Y. Zhang, D. Li, C. E. Montenegro-Marin, and P. M. Kumar. Environmental planning based on reduce, reuse, recycle and recover using artificial intelligence. *Environmental Impact Assessment Review*, 86:106492, 2021.

[31] A. Frankó and P. Varga. A survey on machine learning based smart maintenance and quality control solutions. *Infocommunications Journal*, 13(4):28–35, 2021.

[32] D. Ficzere, G. Hollósi, A. Frankó, and P. Varga. AI toolbox concept for the arrowhead framework. In *19th International Conference on Network and Service Management, CNSM 2023, Niagara Falls, ON, Canada, October 30 - Nov. 2, 2023*, pages 1–7. IEEE, 2023.