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Role of Artificial Intelligence in Mechanical Product and Design

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Abstract: This paper aims to conduct a literature review and analyze the current AI techniques used in product design and development within industries in a competitive manner. With a proper implementation process, AI techniques will positively impact organizations to manage the increasing complexity of products and customers' requirements within a short product life cycle. Manufacturers must process and manage complex information efficiently, effectively reducing time-to-market. These requirements have led to the rise in the application of artificial intelligence (AI) technology in product design and development to manage the process. Also, it attracted significant attention to a new design paradigm called AI-enabled product design. Incorporating AI into the Product Development Process (PDP) facilitates the product design process to be more intelligent, accurately interprets vast data, and achieve specific goals and tasks through flexible adaptation. The paper reviews the AI techniques that set the foundations for PDP development. Subsequently, this paper will cover how AI-enabled design has helped in product design and development, such as e.g., extending product life. Furthermore, it can contribute versatile designs to meet a variety of customer demands since AI can process excess data instantly and provide predictions to optimize product design strategies such as matching mechanisms. With the support of AI technology, manufacturers can develop more effective maintenance and recovery by measurement of their products in real-time. Finally, a conclusion about the advantages/limits of the (AI)- enabled design and future research perspectives are discussed in the last section.

Key Words: *Artificial Intelligence (AI), Product design and development, Predictive analytics*

1. Introduction

Product design and development is a crucial stage for organizations as they determine whether the product produced can be sold successfully in the market effectively and sustainably. The rapid progress in information technology and living standards has shifted product preferences towards customization, as customers now prefer customized products that meet their tastes (Ananto et al., 2021). This phenomenon of customization increases the complexity of products. It demands a short product life cycle, making it necessary for organizations to react quickly, enhance the design effectiveness and efficiency and reduce the time-to-market (Zuoxu et al., 2022) to maintain their competitive advantage. Traditionally, evaluation of customer satisfaction or customers' requirements is only conducted towards the end of the development phase and after the post- launch re-innovation phase. The product redesign at these stages might inevitably lead to an expensive adjustment and potential loss of sales (Cantamessa et al., 2020; Kratschmayr et al., 2015). Nowadays, in the "agile" product design and development context, the gap has been bridged with customers consistently involved at the beginning of the innovation process (Kratschmayr et al., 2015). This is possible through the enabling technology fields from the current digitalization bandwagon that enables objects and people to be connected and engaged. These engagements generate real-time data that allows organizations to analyze, adapt and adjust continuously to address evolving customer needs and technical improvement (Cantamessa et al., 2020), in a collaborative design environment. Nonetheless, organizations need sustainable capacities to integrate and manage the real-time influx of data in reliable and cost-effective methods to support the early decision-making process (Cantamessa et al., 2020). With the appropriate infrastructural support, Artificial intelligence (AI) is leveraged to accelerate the design process by actively supporting human decision- making and performing creative tasks in a timely and cost-efficient manner (Sohn et al., 2021; Zuoxu et al., 2022). This research paper aims to present the application of AI throughout the process of product life cycle management (PLM), supported by different use cases. As mentioned, Zhang et al., highlighted that more than 50% of manufacturing in the future requires customization (Zhang et al., 2017). Thus, it is necessary to explore the possible applications of AI. The paper will start by looking into the current development of AI and its application in PLM and the importance of AI in modern industry practices in Section 2. Followed by two case studies in sections 3 and 4 of different industries, specifically automotive and fashion, will demonstrate the dynamic application of AI. Finally, future research plans to apply AI in product design Section 5.

2.Methodology

1. Literature Review

Conduct a comprehensive review of existing literature to:

Identify AI Techniques: Examine various AI methodologies applied in product design and development, such as machine learning, natural language processing, generative design, and predictive analytics.

Assess Applications: Evaluate how these AI techniques are utilized across different stages of the Product Development Process (PDP), including ideation, prototyping, testing, and manufacturing.

Analyze Outcomes: Investigate the impact of AI integration on product quality, time-to-market, customization, and customer satisfaction.

2. Case Study Analysis

Select and analyze case studies from various industries to:

Examine Implementation: Study how organizations have implemented AI in their product development processes.

Evaluate Results: Assess the outcomes of AI integration, focusing on improvements in efficiency, innovation, and market competitiveness.

Identify Challenges: Highlight any challenges faced during AI adoption, such as data quality issues, integration complexities, and workforce adaptation.

3. Comparative Analysis

Conduct a comparative analysis to:

Benchmark AI Techniques: Compare the effectiveness of different AI techniques in achieving specific product development goals.

Identify Best Practices: Determine best practices for AI integration in PDP, considering factors like scalability, flexibility, and cost-effectiveness.

Highlight Limitations: Identify limitations of current AI applications in product design and development, such as ethical concerns, data privacy issues, and technological constraints.

4. Synthesis and Framework Development

Synthesize findings from the literature review, case studies, and comparative analysis to:

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Develop a Conceptual Framework: Propose a conceptual framework for integrating AI into the PDP, outlining key stages, AI techniques, and expected outcomes.

Provide Recommendations: Offer recommendations for organizations seeking to adopt AI in their product development processes, focusing on strategic planning, resource allocation, and change management.

3. Background

Artificial intelligence (AI) is a system with the capability to adapt that gives high accuracy in analyzing vast amounts of external data sources, process interpreted data, retain and extract knowledge to reach specific goals (Koricanac et al., 2021). The main characteristics and functions of AI technologies are defined as intelligence, systematization, and automation (Azadeh et al., 2016). It resides in the concepts of machine learning and deep learning, which are believed to be important factors that will cause a significant change in many industries around the world (Wang et al., 2021). Modern industries, characterized by global and complex supply chains, are interested in integrating AI technologies to meet mass production demands. The application and incorporation of diverse AI techniques, including genetic algorithms, ontology, nearest neighbor, fuzzy logic, and neural networks can provide efficient decision-making and strategy capabilities in the process of product design and development (Berisha et al., 2021). Overall, it rapidly adapts to market or product modifications from the information exchange at each step of the manufacturing process, providing an efficient and seamless procedure in collaborative operations. Therefore, it can lead different industries including automobiles, fashion, life sciences, and financial services, to efficient, collaborative and automated mass production while minimizing failures. The most benefit of AI-embedded product design and development is that it can provide insights into product lifecycle management (PLM). All products have a lifecycle that begins with design and ends with the manufacturing and service stages. Each step is divided into subsections as shown in Figure 1 (Wang et al., 2021) below, and consists of multiple activities and information. Developing long-term sustainable products would require improvement in the PLM stages. A well-developed PLM incorporating AI capabilities can enhance the capabilities to design long-term solutions. The system can also easily identify outliers and zoned into situations that require changes based on discrepancies from historical thresholds or tolerances (Azadeh et al., 2016). AI is reportedly able to improve product performance during use during the product lifecycle stage. Some examples of these AI tools are shown in Table 1(Wang et al., 2021).

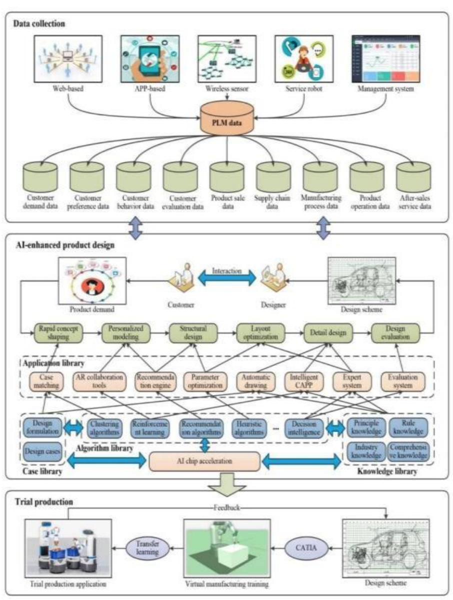

Figure 1 Phases of product lifecycle management.

Figure 2 illustrates an example of an AI-embedded product design process that includes various libraries based on data and knowledge, application, and

algorithm (Wang et al., 2021). The popularity of AI has been created by using it in product design. AI technology provides decision-making support so that product designers can continuously accomplish fast, customized designs. Customers no longer prefer predesigned products; thus, customized production and a flexible supply chain are required.

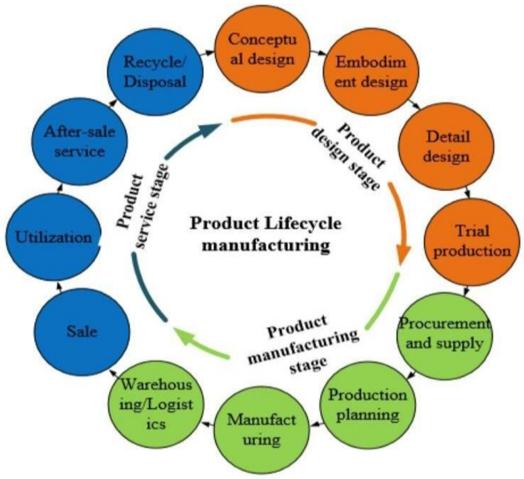

Figure 2 AI-enhanced product design.

This trend has traveled from "Make to stock (MTS)" toward "Configure to order (CTO)" or "Assemble to order (ATO)" manufacturing. In customer-centric supply chains, prediction plays a significant role. AI involvement could achieve a more accurate prediction of customer needs and demands. It could accurately predict product design for customer needs and demands, resulting in smooth and profitable product manufacturing (Koricanac et al., 2021).

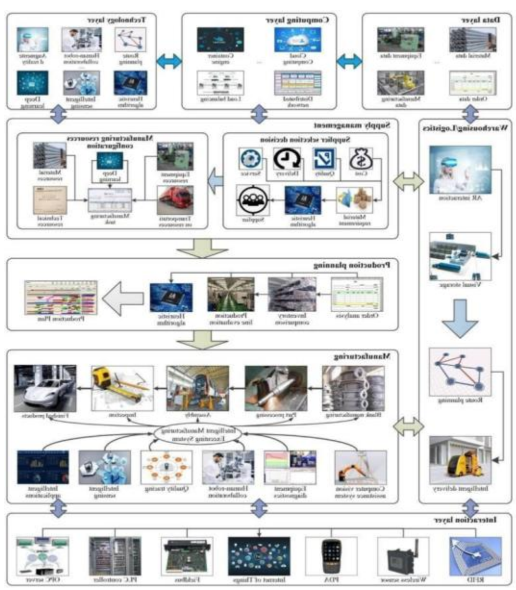

Figure 3 AI-enhanced product manufacturing.

Figure 3 shows an example of an AI-enhanced product manufacturing framework (Wang et al., 2021). AI algorithm is used in production activities and manages procedure optimization and alternating human labor by AI systems. In modern industry, AI can achieve efficient productivity through shortened process cycles and accurate inventory management, thus accelerating continuous improvement across the entire supply chain. For example, Ford faced inventory management issues in May 2018 due to supplier parts delays for its F-150 truck. In 2021, production of the same vehicle had to be stopped again due to a shortage of semiconductor chips. Therefore, automated vehicle production systems based on AI technology are expected to double the production level within the next five years (Wang et al., 2021). Lastly, Figure 4 shows the AI-reinforced services platform of products. There are three main aspects to the service phase of a product supported by AI technology: humanized client service system, remote monitoring, and remote maintenance (Wang et al., 2021). AI can provide efficient product lifecycle management through continuous learning, leading to high levels of accuracy while minimizing uncertainty and failure in production. Therefore, in subsequent Sections 3 and 4, we report on the efficient application of AI in two industries, specifically automotive and fashion.

Table 1 Three stages in product life management

Product lifecycle management phase	**Sub-Phase**	**Related AI tool**
Product design	Conceptual design	Support vector machine (Pal et al., 2016), Semantic clustering (Hu et al., 2012), Fuzzy multivariate decision (Azadeh et al., 2016), Deep residual network (Zhang et al., 2020), and Transfer learning (Zellinger et al., 2020)
	Embodiment design	
	Details design	
	Trail Production	
Product manufacturing	urement and supply	Fuzzy TOPSIS (Junior et al., 2014)
	Production planning	Evolutionary algorithm (Tang et al., 2014)
	Manufacturing	Human-robot synchronization control (Shiboldenkov et al., 2020)
	Warehouse/Logistics	Pick-by-vision system (Schwerdtfeger et al., 2009)
Product service	Sales	Collaborative filtering (Chae et al., 2019)
	Utilization	Natural language processing (Kulkarni et al., 2017)
	After sales service	Wireless heterogeneous sensing (Viani et al., 2013)
	Recycle/Disposal	Cloud recycling system (Wang et al., 2015)

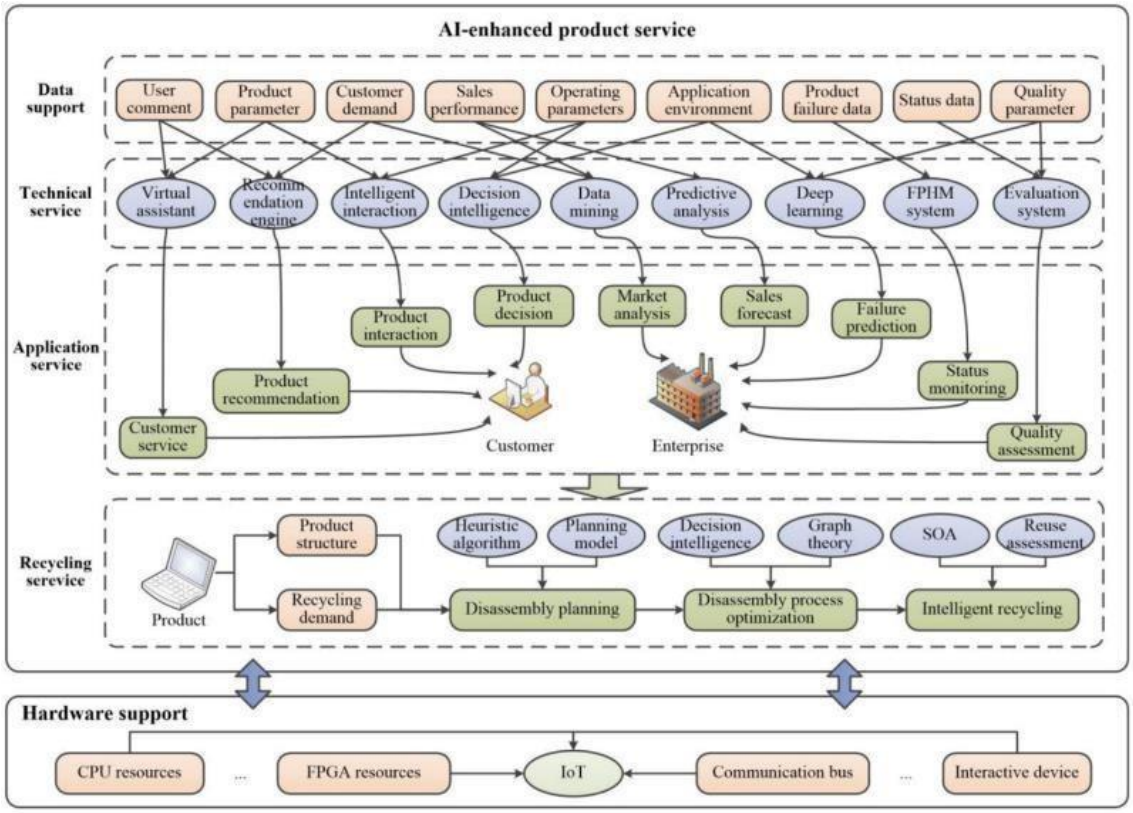

Figure 4 AI-enhanced product service.

4. Case Study: AI for Automotive Industries

The applications for AI are widespread, they can be found across different phases in the automotive industries. Under the current practice, AI is being used in the design, manufacturing, sales, and product maintenance phases of the process for automotive. For example, Mercedes-Benz and Renault were one of the first companies to materialize the AI- incorporated automotive production supply chain (Koricanac et al., 2021). Real-time planning and detection of risk were automatically analyzed and corrected without human intervention. AI technologies enable automobile manufacturers to pre- develop risk mitigation approaches and contingency plans to prevent potential failures or uncertainty. With AI's ability to extract information from large datasets, Mercedes and Renault were able to recognize manufacturing issues even before they occurred. The succeeding paragraphs briefly reviewed and discussed the available studies for AI applied in various phases of an automotive product.

a. AI for product design and manufacturing phase

Recently, AI has been receiving a lot of review and consideration in the latest automotive manufacturing technologies because of its ability to generate strategies and assistance in decision-making for modern manufacturing. It has been reported that AI helps in the optimization of processes, parameters, and quality assessment of manufactured automotive products (Shiboldenkov et al., 2020). Mamun et al., reported the steps of the additive manufacturing (AM) process with the incorporation of cybersecurity as shown in Figure 5 and advantageous to improve the product quality, and cost reduction. Furthermore, AI would be applied to a manufactured product for assistance in decision-making, maximum output productivity, reduction in human interventions, and better communication with customers (Mamun et al., 2022).

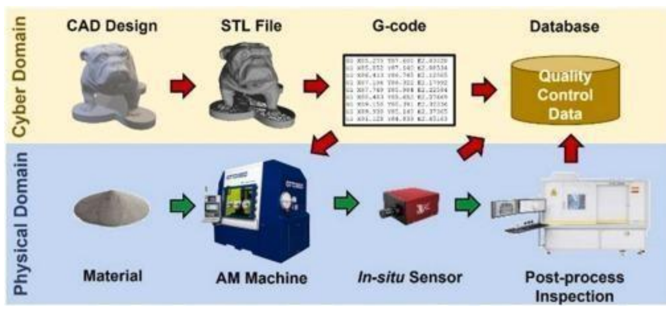

Figure 5 Influence of AI in smart manufacturing for automotive.

b.AI for the product maintenance phase

The AI technology bring together the data and maintenance, which has assisted in inspecting the automotive components parts, conditions, and real- time monitoring. Figure 6 illustrates an AI-embedded quality control system for automobiles that could detect the probability of the requirement for maintenance. Daniyan et al., developed an AI framework that was used to predict the bearing life for automotive component as shown in Figure 7(a). The result explained that the reported AI framework could be advantageous to predict life of a bearing component. The predicted life for a bearing component was 500 hours over the span of 40 days as shown in Figure 7(b) (Daniyan et al., 2021). Hence, AI would be a useful tool to predict life of a component before its failure.

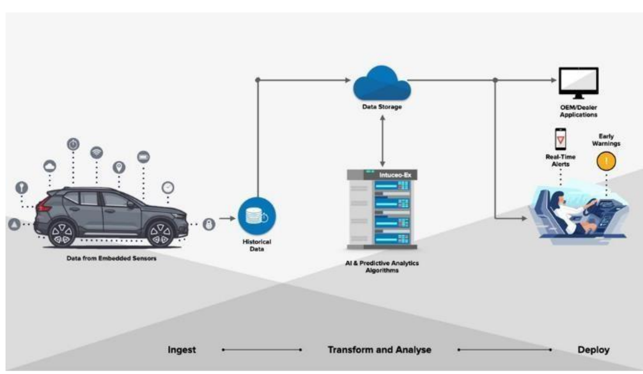

Figure 5 AI embedded quality control system for automotive

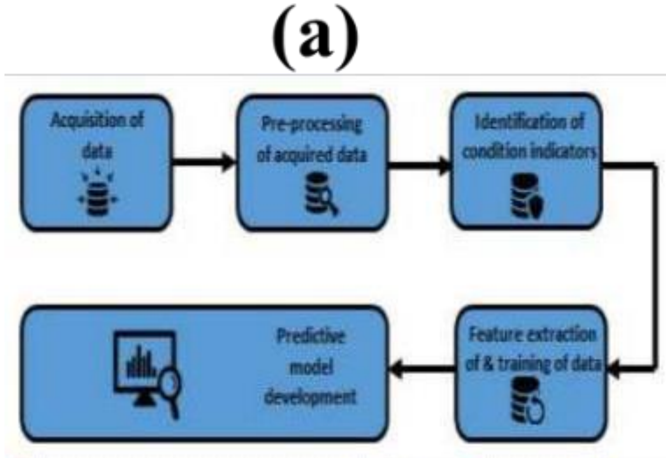

Figure 6 (a) Prediction Process using AI

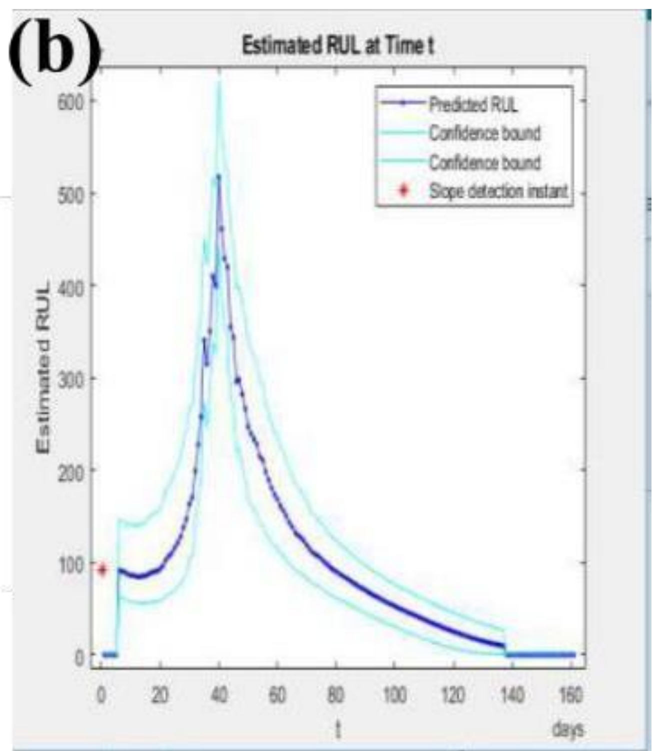

Figure 6 (b) Predicted life using AI framework

b. AI for future Greenfield Automotive

Nowadays, the demand for electrical vehicles manufacturer (such as tesla) continuously increasing due to the strengthening and sustainable development of vehicles (Tsang et al., 2020). To further promote the greenfield automotive, the incorporation of AI techniques is emerging as a solution to their problems such as market risk and product life (Jennings et al., 2016). To achieve the above objectives, Tsang et al., used an AI network to predict the EV product life which consists of three steps named as data gathering, system settings, and decision-making. Figure 8 illustrates the AI based modular framework to management of product lifecycle and strategy for decision-making process. To examine the feasibility of the framework, the authors also implemented this model to predict energy consumption and market demand for greenfield automotive. The results show that the framework had successfully been implemented for the prediction of EV demand in future and their energy consumption as shown in Figure 9 (Tsang et al., 2020).

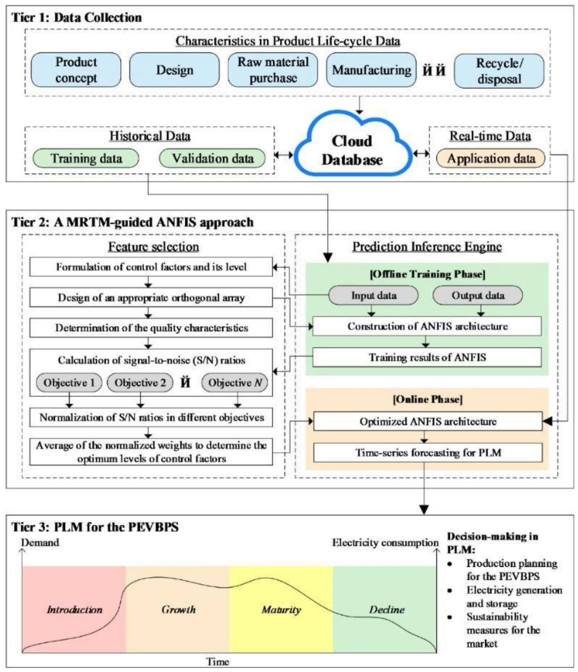

Figure 7 AI modular framework for product lifecycle prediction for EV industries

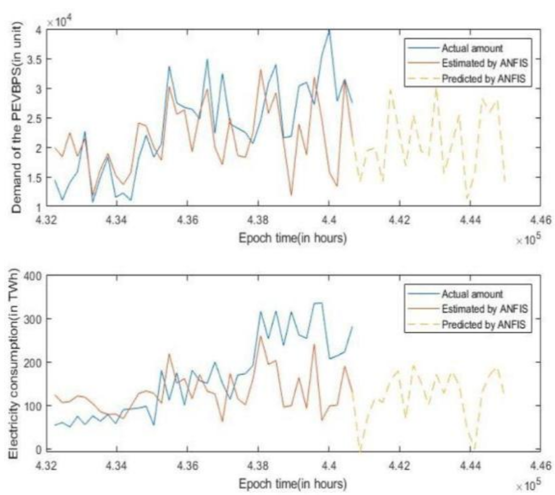

Figure 8 Predicted results for customer demand and electricity consumption using AI Framework

Case Study: Alando's Application of Artificial Intelligence

a. Apparel Design

The fashion industry is also transforming due to AI as it plays essential roles in crucial business processes, from design to the manufacturing stage and supply chain to marketing. We will examine how Zalando, an online marketplace, could provide a world-class customer experience to its 29 million active customers by applying AI in its business processes. The overall direction of the fashion industry's trend is shifting towards 'personalization' (Spirable, 2022) where customers want their purchases to represent their value and uniqueness – the new "luxury." Trends in the fashion industry change rapidly, and designs or patterns are released almost daily, and such changes place intense pressure on designers. Attractive costumes require appropriate clothing designs and patterns of a suitable combination to entice customers to buy, not forgetting the short cycle time required (Zuoxu et al., 2022). Although companies like Zalando offer a wide range of products, creativity for a new design lag significantly due to the time gap between the translation of new trend demand and the ever-changing style.

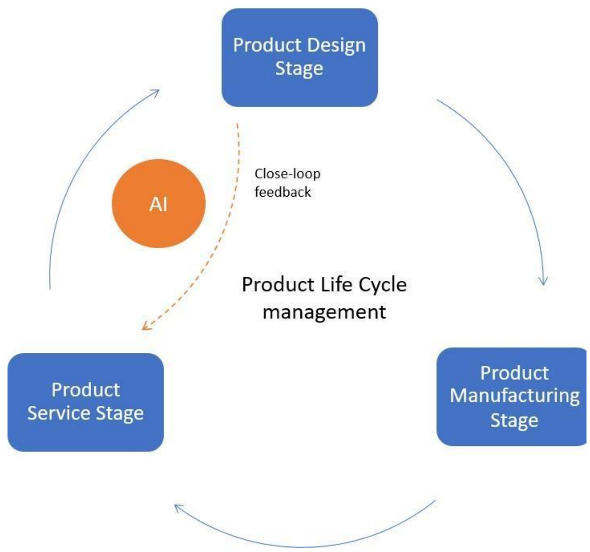

Figure 9 "Close-loop" feedback system

Zalando's vision of "reimaging fashion for the good of all" was aligned throughout the corporate, and emphasis was placed on consistently exploring new and innovative methods to improve their service level and make the fashion world smarter. Zalando has invested in the Human-AI collaborative design as a bridge to create collaborative product design between designers and customers (Rietze, 2016). Figure 10 shows how AI existed within the PLM cycle of Pal's paper (Pal et al., 2016) with reference to Zalando's business model, which makes a close-loop feedback channel that bridges the voice of customers into the product designs stage from the product service stage. This is an example of a collaborative product design process where customers are part of the design process. The voice of customers is obtained in the product service stage and the AI algorithms will analyze and extract key information to recommend designers with the most suitable design to build and launch in the market. AI has the ability to consistently analyze vast amounts of customer data and identify unique styles through the analysis of trending images to identify popular styles and market trends to infuse into the latest design. Based on the customer's favorite colors, textures, and other style preferences – Zalando's Project Muze displayed an application for AI to generate new designs by infusing customers' expectations into future designs.

i. Project Muze

Project Muze is the Human-AI collaborative design by Zalando and Google to develop machine learning algorithms to turn users' personalities and interests into inspirations for unique designs. The primary purpose is to address the gap between the translation of new trend demand and ever-changing style. Project Muze is a cloud base software where users can interact with the AI to generate their own designed clothing.

The approach was to train neural networks (DNNs) with the style preference of more than 600 fashionistas to learn the trend and match with the design that individuals might be interested in and create designs to match them (Rietze, 2016). The DNNs predictive engine is made up of two parts: Neural network and Aesthetic parameters as shown in Figure 11 (Kato et al., 2018).

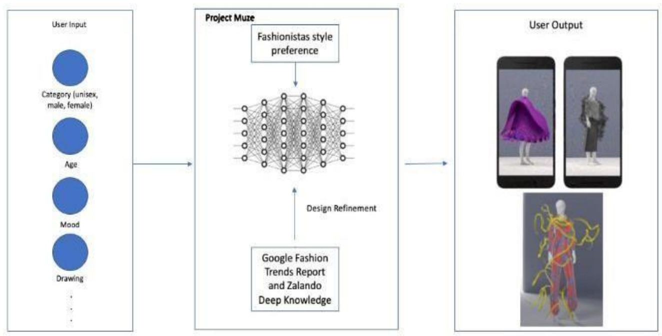

Figure 10 Illustration based on Project Muze.

With the fashionistas' style preference of color, texture, and style preferences, the neural network learns to connect the preference of people based on similar interests. After identifying the preferences, a rough sketch is generated. The first draft sketch will be refined by a set of aesthetic parameters learned from the Google Fashion Trends Report and Zalando's deep knowledge data on fashion (Kato et al., 2018). Based on Figure 11, the project will require users to answer questions such as age and mood and draw some pictures or more; then, based on these inputs, the models will start to generate and create an experimental model. Then it will be refined from the aesthetic parameters to generate a fashionable unique model as shown in the user output. This Human-AI collaborative design successfully developed 40,424 fashion designs within the first month (Rietze, 2016), and 3 virtual designs were transformed into real-life clothing. Integrating AI in product design has been applied in Zalando's business. The application enables Zalando to address the current industry trend of mass customization through the feedback loop that consistently collects feedback and suggestions from customers and creates a collaborative environment for designers. Having AI enhances design effectiveness and efficiency, enabling early decision-making that decreases design and development time and cost. AI's impact on fashion will make Zalando's system more intelligent to process and incorporate the sentiments and fashion tastes of customers into the business processes.

b. Product Recommendation

Along with the Product services, Zalando introduced the Algorithmic Fashion Companion (AFC) model that emphasizes the consumer purchasing journey. AFC suggests outfits matching customers' most recent items in the Zalando Fashion Store and providing a new set of product combinations. The algorithm is developed with training data that tells it what makes a good outfit, envisioning the algorithms to understand fashion and costumes and discern what each customer likes, as shown in Figure 12 below. Based on previous purchases and Wishlist items, AFC will automatically search through the outfit database and provide an AI-human curated outfit that will help customers to design their style. This is also an avenue that AI is closing the loop between product design and product service, where new combinations are proposed to customers. AFC enhances the customer purchasing journey and provides new insights to designers on potential new products that can match with the existing product, a complementary product process.

The AI assists in the designer's journey and complements the users (customers') journey, acting as an "advisor" for both spectrums, improving the shopping experience and Zalando services. AI has redefined Zalando's engagement and interaction with its customers and minimizes the environmental impact while producing fashion at such a fast-changing speed.

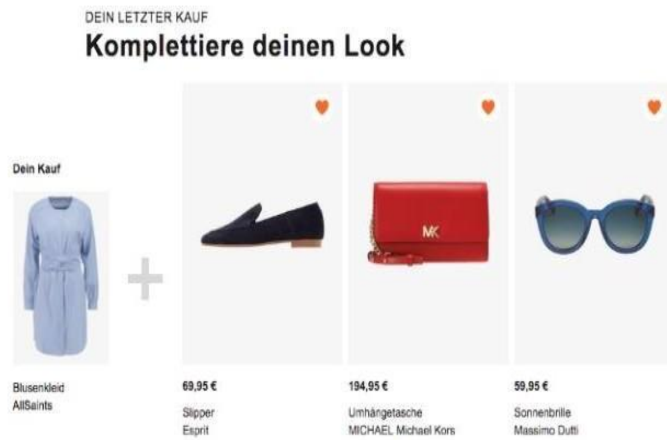

Figure 11 Zalando AFC recommendation system

Conclusion

In this paper, we explored AI-applied product development for lifecycle extension, design, and manufacturing in various industries, such as automotive, textile and fashion. Artificial intelligence (AI) is a tool that learns from data, adapts data flexibility, and accomplishes specific tasks with minimal error. The ability to interpret vast amounts of external data can lead to efficient automated product design and development, from design through manufacturing and service. Well-configured product lifecycle management using AI systems can provide good long- term design. Customers also prefer customized products, so the involvement of AI can better predict customer needs.

To sum up, AI can provide efficient product design and development through continuous learning, leading to high levels of accuracy while minimizing uncertainty and failure in production. We also investigated case studies in the automotive and fashion industries where AI was applied. AI can provide insights into high- volume industries through efficient production system cycles, inventory management, and a service platform.

The tough challenge for AI is to predict and understand a customer’s new needs and intentions, as it is mainly trained based on historical data that does not capture experience that happens elsewhere. AI is a key component of global industries, having a profound influence on product design, customization, manufacturing, and service. We believe that early adoption and successful implementation of new AI technologies will provide significant advantages to product design and development fields.

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