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Enhancing Product Lifecycle Management through AI-Driven Design Optimization

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Abstract
Artificial Intelligence (AI) has recently gained significant traction in the oil and gas manufacturing sector. This study focuses specifically on the oil and gas manufacturing sector. As a key technology, AI has the potential to revolutionize smart manufacturing and the fourth industrial revolution (Industry 4.0). Product Lifecycle Management (PLM) is integral in managing engineering, business, and operational processes for products throughout their lifecycle. By leveraging AI, companies can enhance decision-making processes that align with economic and environmental considerations. This study investigates AI's role in the design phase of PLM within the oil and gas sector. The objective is to evaluate AI's benefits in design optimization and its influence on decision-making. A Delphi-based survey was conducted among 62 experts from multinational oil and gas firms. The findings indicate that AI significantly improves design efficiency, visualization, and prototyping. However, the study highlights integration challenges, data security concerns, and limitations in current industrial communication protocols. Further research should explore AI's role in the remaining PLM phases and its integration with existing IT infrastructures. Future research should extend to the remaining phases of PLM not covered in this study and address limitations such as integration with existing IT systems and improvements in industrial communication protocols.

Keywords
Artificial Intelligence, Product Lifecycle Management, Sustainable Production, Decision Making.

Introduction

Product Lifecycle Management (PLM) is an industry process concerned with managing the complete life cycle of a product from conception through engineering, design, manufacturing, service, and disposal (Zhou et al., 2018). Innovations in information technology – including the Internet of Things (IoT), cloud computing, and AI – are evolving the concept of advanced manufacturing by influencing all aspects of PLM (Tao & Qi, 2019) Initiatives under Industry 4.0 and similar industrial revolutions around the world are accelerating this trend (Li et al., 2017), exemplified by the deep integration of AI into manufacturing.

Design decisions in early stages can contribute to more than 80% of the total cost and performance of a product across its lifecycle, making the design phase the most critical part of PLM (Bernard et al., 2014). Additionally, rapidly changing customer requirements and market demands put pressure on manufacturers (especially small and medium enterprises, SMEs) to release novel products in record time (Zhang et al., 2020). This drives product development toward a human-centered, data-driven design model, making it imperative to successfully collect, share, and manage all data required in the design stage of complex projects (Niu et al., 2021). However, many manufacturing firms (particularly in the oil and gas sector) struggle to fully utilize "Big Data" in PLM. Challenges such as insufficient data storage capabilities and lack of knowledge to use collected data mean that valuable information is often not properly stored, transmitted, or shared (Li et al., 2015). Big Data analytics should penetrate all phases of the manufacturing value chain to reduce product development time, enhance processes,

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and meet customer needs, especially in aggressive markets where time-to-market is critical (Roy et al., 2016).

Digital twin technology has emerged as a means to virtually model products and processes. Powered by Big Data and IoT, digital twins can substitute for costly, time-consuming physical prototypes during the design phase, allowing realistic evaluation of design decisions (Altintas et al., 2014; Schleich et al., 2017). AI, broadly defined as computer systems' ability to perform tasks normally requiring human intelligence, has rapidly proliferated alongside Big Data and Machine Learning (ML) techniques ((Borana, 2016). A distinctive feature of modern AI is its ability to replace or augment human operators in complex tasks, increasing reliability, accuracy, and efficiency. AI applications span many sectors (automotive, healthcare, etc.) (Iansiti & Lakhani, 2020), and manufacturing firms are increasingly embracing AI-centric operational models where key processes are digitized to reduce human labor. For example, AI algorithms already set prices on e-commerce platforms and determine loan eligibility in finance, while humans focus on developing and maintaining these algorithms ((Verganti et al., 2020). These advances underscore that AI has potential to reshape industrial workflows.

In this study, the PLM model is considered in three primary stages: design, manufacturing, and service. The study focusses exclusively on the design phase of PLM in the oil and gas engineering and equipment manufacturing context. Based on the literature, this research examines the consequences of utilizing AI (along with abundant Big Data and digital twin technology) in the design stage. The scope of this work is industry-specific: it concentrates on the oil and gas sector, and findings may not directly generalize to other industries. This narrow focus allows an in-depth analysis of AI's impact on a critical phase within a particular industrial context.

Research Purpose and Hypothesis

The purpose of the study is to evaluate how AI can enhance the product design phase of PLM in the oil and gas sector. It is hypothesized that integrating AI into the design stage will significantly improve design efficiency and decision-making quality in oil and gas equipment manufacturing. Research Questions: Based on gaps identified in prior research, the study addresses the following key questions:

1. To what extent can AI affect the design phase of PLM in the oil and gas industry? (For example, how much can AI accelerate or improve design workflows?)
2. Which design decisions can be handled by AI, and which still require human intervention? (Identifying what aspects of design AI can automate or support versus areas where human expertise remains essential.)
3. Which aspects of the design stage can be enhanced the most by AI implementation, and which aspects cannot be effectively enhanced by AI? (E.g., can AI assist more in concept generation, in engineering analysis, in prototyping, etc., and are there limits?)
4. How ready is the oil and gas sector to adopt AI in design, and will such adoption require changes in business structure or roles? (Assessing industry openness to change and potential organizational/hierarchical shifts due to AI integration.)

By answering these questions, the study seeks to fill the gap of AI applications focused specifically on one PLM phase (design) in a particular industry. Previous research often discussed AI in PLM broadly or in other domains, but rarely isolated the design phase in oil and gas. A clear focus on this phase and industry will help determine the feasibility and implications of AI-driven design optimization in practice.

Literature Review

PLM and the Importance of the Design Phase

The concept of PLM was introduced to describe a product transformation in the market. PLM was divided into three stages, promotion, maturity, and decline. With the introduction of contemporary engineering practices in 1980, PLM successively penetrated the manufacturing field. PLM evolved to include analysis of the market, design of the products, development of the processes, manufacturing, supply chain management, customer service management and finally end of life stage (Ranasinghe et al., 2011). To gain value from PLM, companies must truly embed PLM concepts into their processes and ensure data flows seamlessly through design, manufacturing, and service stages**.** Several models for PLM exist and each model divides it into different number of stages. To describe the processes and methodologies of applying AI on the design stage, the simples PLM model will be selected where it is divided into three stages, design, manufacturing, and product stages. The design stage is also split into smaller stages as shown in Fig. 1 and 2. The design stage consists of the design concept, preliminary design, design detail, and prototype.

Fig. 1. Product Lifecycle Management

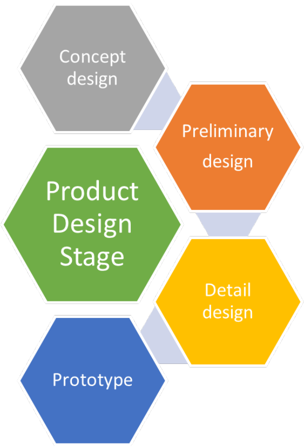

Fig. 2. PLM Design Stage

The Development of PLM

PLM was created to complement the functions of design and manufacturing software and tools. These tools include computer aided design and engineering (CAD and CAE). PLM evolved from the tool period to the integrated application age and finally to the cooperative ecosystem period. In response to changes in the business environment, management, and manufacturing processes, new technological aspects were devised, improved, and integrated, eventually culminating in the existing iteration of PLM. PLM is on the verge of becoming a critical piece of information infrastructure. Manufacturers may incorporate cutting edge technologies in areas such as the collection and processing of product information, the management of customer preferences and behaviors, and the optimization of company workflows and processes (Wang et al., 2021). The actual implementation of PLM relies greatly on an all-inclusive information structure that combines diverse data, information, and systems. The combination of such information in PLM broad requires theories and approaches, related technologies that manage information interaction, data mapping, experience and, internet services (Tao et al., 2018a).

Implementation of PLM

The implementation of PLM depends on a complete information model that integrates an amalgamate of data, information, and systems. Many firms have implemented PLM but cannot realize its benefits due to lack of its usage. While PLM helps increase the productivity and performance of a firm, it's benefits can be only realized if the PLM concepts were integrated into the business practices and processes (Singh et al., 2021). PLM is concerned in managing the product lifecycle through data obtained along the products life stages starting from design passing through manufacturing and ending with service. Multiple data frameworks, simulations, and process models for integrating numerous PLM aspects have been suggested (Lyu et al., 2017).

The Importance of The Design Stage of PLM

As a result of a fast-changing market and customer requirements, product design has transformed into a data-driven design model that is customer-focused. The design process is becoming more complex as crowdsourcing is usually involved keeping in mind that this process will involve the complete lifecycle stages of the product. Thus, it is imperative to successfully collect, share, and manage information related to the design stage in those complex design processes. Customer needs and the demands of the market which are continually growing and changing over time are putting great pressure on manufacturing related small and medium business enterprises (SMEs) thus challenging those business to release a variety of new products in a short time (Gauss et al., 2021). Therefore, new product development (NPD) has become a critical indicator of the survival of an organization. It also gives the organization a competitive advantage (Hadaya & Marchildon, 2012). Manufacturers are currently understanding that customer retention and loyalty can be realized by superior product design and ultimately leading to market dominance. Product design is now utilized to develop to continual and everlasting relationship with the clients. Acknowledging the importance of the design stage of PLM has begun to deliver its advantages (Gilal et al., 2018).

The New PLM Requirements

The requirement for high quality products and new innovations, keeping in mind the cost-effectiveness of the design, is pushing PLM to its limits, and imposing new requirements. Manufacturers should shorten the life cycle process of the product especially the design and manufacturing phase to ensure a fast time to market approach. They need to develop a customizable, adaptable, and responsive design. Manufacturing networks should be developed to ensure collaboration between relevant stakeholders and share available resources. The intelligence of the design and manufacturing process must be enhanced to ensure higher quality products and shorter lead times. Process automation should be valued against traditional processes. The availability of a huge volume of industrial data forces manufacturers to employ new methods to acquire, mine, and utilize this data. To realize the evolving constraints for PLM industries and academia are devoting enormous effort to utilizing new technologies such as AI and digital twins (Tao et al., 2015).

Artificial Intelligence

AI is the intelligence demonstrated by an artificial being or entity utilized to solve complex algorithms. Such a system is usually attributed to be a computer or a machine. Artificial intelligence is the amalgamation of computer science and physiology. It is the ability to generate results in our current world using computational algorithms. It is being able to mimic human intelligence to make choices and adapt to the learning experiences. This approach is an attempt to make computers more human-like but at a faster pace. Thus, AI is divided into two parts, strong and weak AI. Other more diverse classification of AI divides it into three categories, narrow intelligence (ANI), general intelligence (AGI) and super intelligence (ASI) (Gobble, 2019). AI categories also have subdivisions that are common between them but vary significantly is strength and application. Those subdivisions are perception, logic, learning, and behavior. Fig. 3 illustrates those subdivisions.

Perception

Computers interact with the outside environment and evaluate sensory input through perception. Today's smart devices include a range of IoT modules, such as cameras, sensors, and microphones, which enable them to gather structured and unstructured data from the outside world. Therefore, the traditional model-based approach to intelligent perception is be-

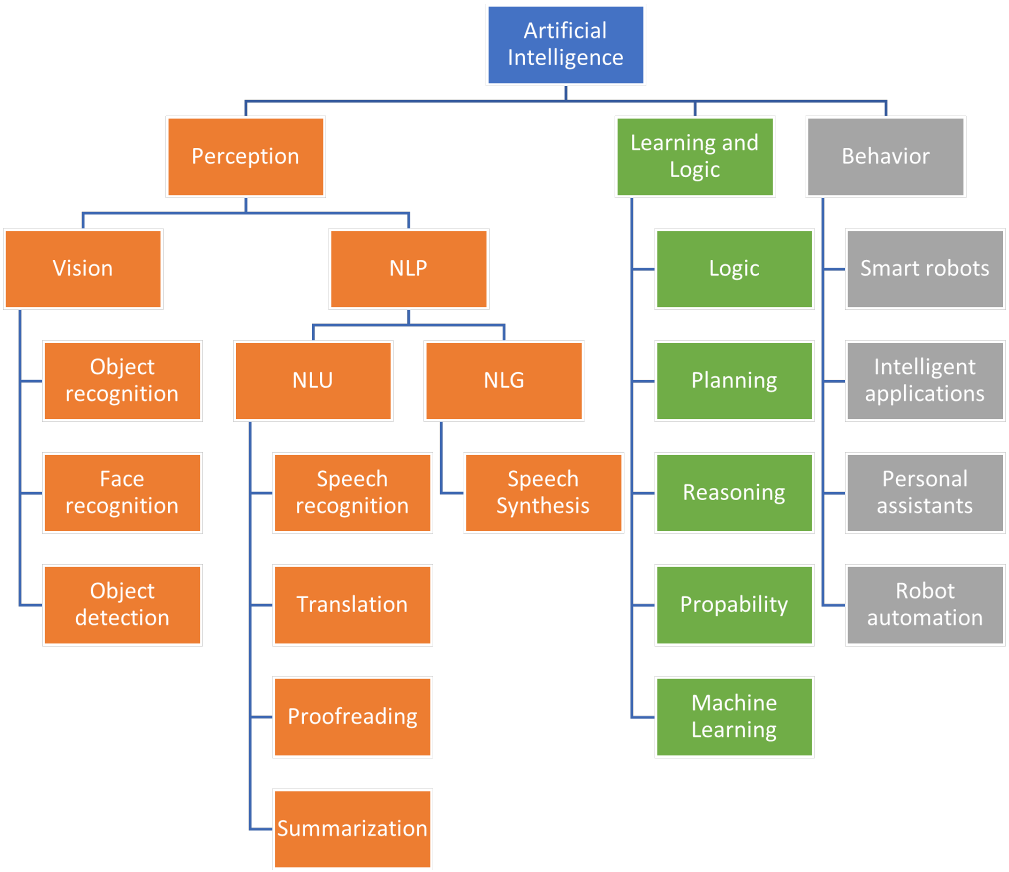

Fig. 3. Artificial Intelligence Characteristics

ing phased out in favor of a data-driven one (Fast & Horvitz, 2025). Computers can nowadays extract data and create deep understanding based on the unprocessed data it gathers from images and video. This is referred to as computer vision. This type of perception is dedicated to collecting data from features that are characteristics of images or video. The data AI can extract can be detection of shapes, edges, corners, and colors (Bao et al., 2019). This information can be collected using several deep learning convolutional neural networks (CNN) (He et al., 2019). Another feature of AI that can enable computers to interpret speech is called natural language processing (NLP). This feature allows computers to understand human speech using natural language understanding (NLU) algorithms and generate natural speech using natural language generation (NLG) algorithms (Sainath et al., 2017).

Learning, Logic, and Behavior

AI has the ability to learn then evaluate in order to pass judgement and make proper decisions based on the acquired information. Logic was a complex subject even before the emergence of AI. The broad rules regulating the reasoning that supports distinct instances of problem resolution are referred to as logic. It overcomes problems with clever thinking and makes it easier to analyze, characterize, and program, as well as describe and imitate intelligence. Probabilistic logic and first-order logic are included in the area of logic known as common logic. A powerful learning and logic engine is the one that Netflix utilizes. Their machine learning algorithms use three statistical methods called supervised, unsupervised, and reinforcement learning. Using supervised learning the AI tries to become as close as possible to an expert. Similar to analyzing a picture to detect its contents by an expert, the AI creates a labeled dataset of the picture contents. This data is split into training and validation data, where the AI compares the predictions with an expert. If the results are not satisfactory, new data can be collected. The integration of the computer perception is used to control the behavior of AI (Webster & Ivanov, 2020).

Use of AI with PLM Design and Research Gaps

AI has become an integral part of manufacturing and services, primarily embedded within existing products rather than contributing directly to their design. Processors such as Apple's A-series Bionic chips and Google's Tensor chips enhance AI capabilities in mobile devices but do not actively influence product design. Research into AI's role in PLM design has explored various applications. Ning et al. proposed a 3D Convolutional Neural Network (CNN) for part-feature recognition, demonstrating AI's potential in estimating product costs based on component complexity (Ning et al., 2020). However, their study lacks details on how neural networks influence cost estimations across varying design complexities.

Baride (2025) explored the evolving role of Artificial Intelligence in reshaping Product Lifecycle Management, with particular attention to how AI tools can streamline operations and support more strategic, data-informed decisions throughout the product journey. The study situated Generative AI not merely as a technical add-on, but as a core mechanism for accelerating design iterations, improving visibility across lifecycle phases, and enhancing the overall quality of product launches. Rather than advocating a wholesale disruption, Baride framed AI as a catalyst for a more responsive and agile approach to PLM transformation. Verganti (2020) highlighted a paradigm shift where AI is directly integrated into design decision-making, reducing human involvement in detailed design tasks. This approach is exemplified by Tesla's sensor-driven AI models that continuously refine vehicle design through real-time data collection (Verganti et al., 2020). However, such implementations remain industry-specific, limiting broader applicability.

Li et al. examined AI's integration with Big Data across PLM's three phases – design, manufacturing, and service. AI-driven marketing analysis and predictive maintenance show promising results in enhancing design by incorporating customer insights and operational data (Li et al., 2015). Nonetheless, challenges such as data confidentiality in the oil and gas sector, data storage constraints, and encryption needs pose barriers to AI adoption in PLM.

Kwang et al. used chaos-based fuzzy regression to assess AI's ability to optimize consumer product design through market-driven surveys. Their study found AI could predict optimal design specifications with 7.79% Mean Absolute Percentage Error (MAPE) (Kwong et al., 2016). However, its application was limited to household items, raising questions about scalability for industrial products.

Tao et al. (2018b) introduced digital twins as a method to synchronize physical and virtual models throughout PLM. Their case studies demonstrated AI-driven design optimization for bicycles and CNC machining. However, their research overlooked high-performance computing requirements and real-time synchronization challenges in large-scale manufacturing.

Despite growing research, most studies focus on AI's role across all PLM phases rather than specifically on the design stage. Existing models fail to address

AI's integration in engineering-heavy industries like oil and gas, where design iterations depend on highly sensitive operational data. Furthermore, studies lack a comprehensive framework detailing AI's role in decision-making, constraints in human-AI collaboration, and challenges in data-driven design methodologies. This study aims to bridge these gaps by examining AI's specific impact on the design phase, identifying AI-handled tasks, and determining areas requiring human intervention.

Emerging PLM Requirements

As global competition intensifies and technological advancements accelerate, PLM must continuously adapt to new industry demands. Several key challenges are reshaping PLM requirements, including:

- Accelerated Product Development: Reducing design and manufacturing lead times to ensure a faster time-to-market.
- Adaptive and Customizable Designs: Enhancing flexibility to support personalized and user-driven product configurations.
- Collaborative Manufacturing Networks: Establishing integrated supply chain systems to improve communication and resource-sharing among stakeholders.
- Intelligent Automation: Incorporating AI-driven automation to refine design processes, optimize production, and ensure quality consistency.
- Data-Driven Decision Making: Utilizing AI and Big Data analytics to support predictive maintenance, optimize production schedules, and enhance operational efficiency.

Industries and research institutions are heavily investing in next-generation PLM solutions, particularly focusing on AI-enhanced analytics, digital twin simulations, and automated decision-making tools. These technologies are expected to revolutionize PLM by improving efficiency, reducing development costs, and enabling more agile product design strategies (Tao et al., 2015).

Methodology and Design

To gather opinions from experts on this specialized topic, a Delphi consensus approach was employed (Drumm et al., 2022; Hsu & Sandford 2007). The Delphi method is well-suited for leveraging expert knowledge to predict trends, set priorities, develop ideas, or solve problems when empirical evidence is limited and human judgment is critical. Given the exploratory nature of our research questions, Delphi was chosen to build consensus on what benefits and challenges AI presents in PLM design for oil and gas.

Delphi Process: Three rounds of surveys with a panel of selected experts were conducted. (Delphi studies typically use 2–4 rounds; three rounds were used here because consensus was achieved by the third round, making a fourth unnecessary and avoiding respondent fatigue. This is in line with Delphi best practices, where 70–80% agreement often signifies consensus? An electronic Delphi (e-Delphi) format was employed, using online survey platforms, email correspondence, and video conferencing to facilitate communication. Each successive round was structured to build upon the findings of the previous one, as outlined below:

- Round 1 (Brainstorming): An initial online questionnaire (via Google Forms) with several open-ended questions was distributed to the expert panel. These questions prompted participants to freely identify potential benefits, applications, and obstacles of AI in the PLM design phase. Experts had two weeks to submit responses anonymously. This round aimed to uncover the broad range of relevant topics and gather diverse ideas for subsequent exploration. The preliminary questions were validated by the participants for clarity, and they had the opportunity to suggest additional issues or topics that the study should address?
- Round 2 (Narrowing & Consensus Building): Based on Round 1 input, the researchers compiled a preliminary questionnaire listing specific statements and items derived from the experts' feedback. This draft questionnaire was shared with all panelists prior to a group discussion. Then, moderated Microsoft Teams meetings were held (in smaller groups as needed for availability) to discuss each proposed questionnaire item in depth? During these sessions, the moderator presented a summary of Round 1 results and each item while ensuring participant anonymity in expressing opinions. The experts indicated whether they agree or disagree with each item as a relevant statement to include. If there was disagreement, the item was debated. An item was considered approved if it achieved over 80% agreement among the panel? The moderator facilitated these discussions to ensure balanced input, prevented any single individual from dominating, and used the 80% threshold to quantify consensus. By the end of Round 2, the questionnaire was refined to reflect only those statements and questions that the panel collectively agreed were important and clearly formulated.
- Round 3 (Confirmation): The revised questionnaire (after Round 2) was sent out again to all participants for independent review and final feedback.

This round allowed experts to reevaluate the refined questions without group influence. Unanimous agreement (100%) on the final draft was achieved in Round 3, confirming that the wording and content of each question had the panel's full support? At this point, the Delphi process concluded with a finalized survey instrument ready for broader data collection.

Participants

The study's expert panel consisted of professionals selected for their experience in PLM and AI within the oil and gas manufacturing sector. Participants included product lifecycle managers, engineering managers, senior engineers, and other specialists with >10 years of experience in oil and gas design or operations. All experts voluntarily agreed to participate and they were drawn from a single multinational oil and gas equipment engineering firm, ensuring a consistent industry context. The company has global operations; our panelists represented various business units (e.g., design, manufacturing, service departments) in multiple countries, including regions in North America, Europe, and the Middle East. Invitations were sent via email along with study information and consent details. To encourage open and unbiased feedback, participants' identities were kept confidential from each other (only the researchers knew the roster). This anonymity within the group helped mitigate dominance or conformity effects, especially important in Round 1 when generating ideas freely?

A total of 63 experts were invited and 63 participated in at least one Delphi round, though 62 experts completed the final survey. This high retention reflected strong engagement from the panel.

Questionnaire Development and Structure

The final survey questionnaire, as established through the Delphi process, contained structured questions aligned with our research objectives. It was organized into sections covering:

- AI Benefits and Applications in Design – statements describing potential advantages or uses of AI in the design phase (e.g., "AI can improve root-cause analysis of field failures to enhance design decisions") which respondents rated
- AI and Decision-Making – items probing the extent to which AI should make autonomous decisions in design (e.g., "AI systems should be allowed to make certain design decisions without human approval")
- Design Aspects for AI Integration – a multi-choice or ranking question asking which design-stage activities (such as market analysis, 3D visualization, prototype testing, etc.) would benefit most from AI (this corresponded to Fig. 4 in results)
- Challenges and Barriers – a series of statements about potential challenges (data availability, integration cost, security, skills gap, etc.) that respondents evaluated in terms of significance
- Organizational Impact – questions on whether AI adoption would require changes in roles, training, or organizational structure

Data Collection and Analysis

The final questionnaire was emailed to all panelists after Round 3. Sixty-two responses were received from the manufacturing, service, and engineering departments of the firm (a response rate of $\sim 98\%$). The survey platform recorded responses anonymously. The data were exported to IBM SPSS for analysis. Given the nature of the questions, both descriptive and inferential statistical analyses were conducted:

- Median and interquartile range (IQR) were calculated for key Likert-scale items to summarize the central tendency of expert opinions and assess the degree of consensus variability. The median represented the middle value of the sorted responses, while the IQR – defined as the difference between the 75th and 25th percentiles – measured the dispersion within the central 50% of responses. A narrow IQR was interpreted as a strong indication of consensus among participants. For each identified challenge, both the median agreement and corresponding IQR were computed to evaluate the uniformity of panel responses.
- Frequency distributions were examined for categorical items. For example, the proportion of respondents who agreed or disagreed with the proposition that AI should make autonomous decisions was calculated and presented (see Results, Table 4).
- Correlations between selected variables were explored to identify potential relationships. Specifically, the association between "time to AI adoption" and "time to see impact" was analyzed. A linear regression was conducted with "time to see impact (benefit)" as the dependent variable, and predictors such as adoption timing and data collection maturity were included to quantify their influence on expected outcomes.

Statistical significance was assessed at the 0.05 level. While the Delphi moderation process was qualitative in nature, by Round 3, full consensus had been achieved, with 100% agreement on all items. As a result, no further application of formal consensus metrics was required beyond that stage. The combination of Delphi for questionnaire development and statistical analysis for the final survey results provides both qualitative consensus insights and quantitative evidence for our research questions.

(Note: The original survey instrument is not appended here in full; however, a reconstructed sample of representative questionnaire items is provided in Appendix A to illustrate the question formats and content.)

Outcomes

The final questionnaire received 62 responses from the manufacturing, service, and engineering departments of oil and gas equipment manufacturing company. The answers were imported into SPSS and analyzed for correlation using regression. The survey revealed both opportunities and challenges, as well as the correlations between them. The outcome of the survey was also discussed during an interview with two SMEs in the oil and gas equipment manufacturing domain.

AI in Predictive Maintenance and Product Design

One clear theme was that AI can bridge data from product operation back to design improvements. Many respondents noted the difficulty for humans alone to analyze the growing volume of sensor and IoT data from equipment. AI's "learning and logic" capabilities (particularly deep learning) are increasingly important to digest this data and determine root causes of equipment failures. The survey and follow-up expert interviews indicated strong agreement (median agreement = 5 on a 5-point scale; IQR = 1) that AI-based analytics on field data (e.g., machine performance, failure incidents) can feed valuable insights to designers. For example, if an AI performs root cause analysis on failures, the results can be relayed to design engineers to suggest solutions. Design improvements can then be implemented and virtually tested based on these insights. Participants gave examples such as AI creating dynamic maintenance schedules from historical failure data, which in turn allows design teams to reinforce frequently failing components. This finding aligns with prior expectations that using AI for predictive maintenance data will help designers refine product reliability earlier in the design cycle.

Effects of AI Adoption Time and Data Collection

The rapid improvement of AI technologies means that early adopters might gain benefits sooner. Our analysis of the survey data showed a strong relationship between how early a company adopts AI and how quickly it reaps the benefits in design efficiency. In particular, respondents who indicated their organization was adopting AI sooner tended to also report a shorter expected "time to see impact" from AI. To quantify this, a regression analysis was performed. Table 1 presents an ANOVA summary for a model predicting the time to see impact (dependent variable) from two independent factors: time to adoption of AI and effectiveness of data collection in the company. The model yielded a highly significant result ($p < 0.001$), indicating a reliable linear relationship? The F-statistic of 24.217 with df = 2.59 confirms the model's overall significance.

Table 2 shows the regression coefficients. Both predictors had $p < 0.01$, indicating they significantly contribute to the model? The coefficient for time to adoption is positive ($B = 0.898$, $p < 0.001$), meaning that a longer wait to adopt AI is associated with a longer time to see benefits (essentially, delayed adoption leads to delayed benefits). In contrast, the coefficient for data collection is negative ($B = -0.378$, $p = 0.009$), suggesting that better data collection practices correlate with a shorter time to realize AI's impact (i.e., more comprehensive data collection accelerates the benefits). In summary, the regression equation (Equation 1) implied that companies which invest in AI sooner and have strong data collection mechanisms can expect to see design improvements faster, whereas lagging in adoption or lacking data will prolong the wait for benefits.

Table 1
ANOVA results for regression model

Model		Sum of Squares	df	Mean Square	F	Sig.
1.	Regression	31.042	2	15.521	24.217	$< 0.001^b$
2.	Residual	37.813	59	0.641		
3.	Total	68.855	61			

1. Dependent Variable: time to see impact
2. Predictors: (Constant), Data Collection, time to adoption

Table 2
Model Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1.	Constant	3.178	0.829		3.834	< 0.001
2.	Time to adoption	0.898	0.200	0.486	4.495	< 0.001
3.	Data Collection	–0.378	0.140	–0.293	–2.707	0.009

T_{benefits} = 3.178 + 0.898\cdot T_{adopt} −0.378\cdot\text{Data Collection} (1)

The R Square value of 0.451 of the model in Table 3 signifies that 45% of the variation in the dependent variable "time to impact" is explained by the change in the independent variables, time of adoption and data collection, while 55% of the changes are due to factors that are not yet known. This analysis quantitatively reinforces the experts' qualitative opinions: starting early with AI and investing in data infrastructure pays off in terms of quicker realized advantages in product design.

AI and Decision Making

There was a great agreement between the participants of the survey that AI cannot be allowed to participate in decision making. Table 4 below shows the 75.8% of the participants either disagree or completely disagree that the AI should be allowed to take decisions. The results are because that the company wants to adopt a supervised AI where the AI will be allowed to give recommendations to improve the product design which are then presented to a subject matter expert who will validate the recommendations and either reject them or approve them. These decisions may include what material to be used, the specification of the material and the quantity. For example, in a mast design the decisions would be electing to use a suitable steel grade. This type of adoption is required from a legal point of view as who to be held responsible if there was a design fault in the design that might cause injury or death. This level of control might be changed in the future and AI will be allowed to make the decisions.

AI and the Business

A high-quality product ultimately bring benefits to the oil and gas equipment manufacturing as a whole. This is achieved by improving the manufacturing process by implementing intelligent manufacturing processes such as computer vision and robots. Smart manufacturing solutions are becoming increasingly prevalent in order to increase shop floor cooperation and intelligently plan, coordinate, and alter a complicated production process with little human interaction. AI can be also used to simulate the production process and effectively detecting manufacturing problems or even equipment failure. Advancements in IOT has made that possible as data can be collected from existing machines which can allow the AI to create a manufacturing model which it can use. Possible design categories can benefit from AI. Fig. 4 below shows the categories.

Analysis of market demand, visualization of the design in simulated 3D environments, and design improvements are the most agreed upon areas of the design phase that can be targeted by AI implementation. Digital marketing is significantly impacted by artificial intelligence. Consumers believe that businesses should understand their customers' wants and expectations. Manufacturers may utilize AI marketing to quickly analyze a massive quantity of marketing data from social media platforms, customer surveys, and the emails. As a result, AI marketing is a must for all businesses. Data visualization uses methods to construct concepts that are familiar with humans to understand.

Table 3
Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
				R Square Change	F Change	df1	df2	Sig. F Change
0.671[a]	0.451	0.432	0.801	0.451	24.217	2	59	< 0.001

a. Predictors: (Constant), Data Collection, Time to adoption

Table 4
Decision Making

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree	10	16.1	16.1	16.1
	Disagree	37	59.7	59.7	75.8
	Neutral	8	12.9	12.9	88.7
	Agree	7	11.3	11.3	100.0
	Total	62	100.0	100.0	

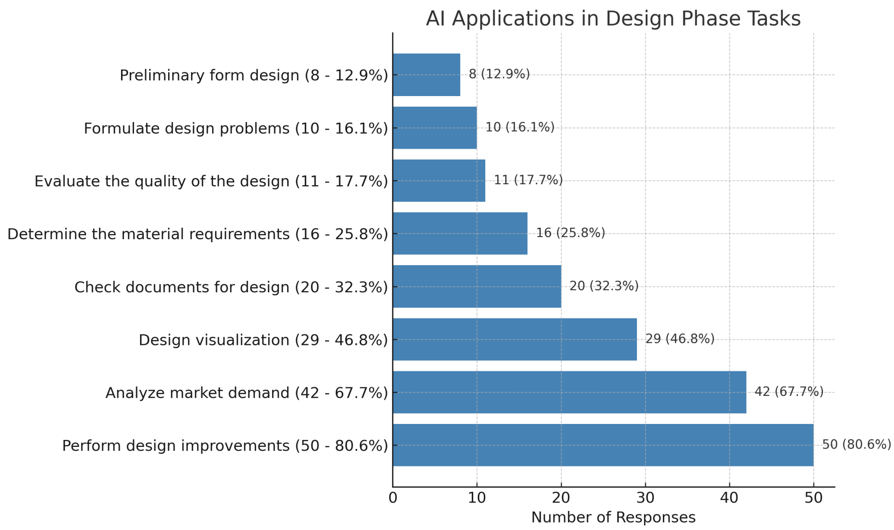

Fig. 4. Design Categories

Such artificial intelligence platforms can combine the data collected from customer surveys to create a new drilling equipment design. Such an approach can be done by compiling data from questionnaires about existing equipment, the Top Drive for example. The Top Drive is the main drilling tool on modern drilling rigs. It is essentially similar to hand drill but hundreds of times bigger. The top drive comes in different sizes and capacities with several features for customers to use. Collecting data about several Top Drive models and makes from the users will create a benchmark that can be fed into the AI to suggest design improvements and additional useful features that would satisfy the customers' requirements. The AI can then visualize the new product in a 3D environment that could be used to simulate usage and evaluate the AI suggestions.

Challenges

Although implementing AI in product design there are several challenges were observed. The survey data has revealed multiple challenges that might delay or even hinder the implementation of AI. The most notable difficulty pertained to data, integration costs and lack of experienced personnel.

Data availability, collection, and storage

AI performance depends strongly on huge data available for training. This data will come from cognition and perception. As the size of raw data increases it becomes increasingly difficult to validate the consistency of the data. That also adds to the complexity of the AI algorithm that will increase in direct proportion to the data. Thus, a great challenge is the proper collection of high-quality data. This data will also require large storage capacities and might require real-time transfer from end to end.

In the oil and gas industry, it is very difficult to collect data related to equipment functionality and failures. This challenge is due to the nature of the business or the environment where the equipment operates. Most of the drilling operations occur in locations that are far from civilization, such as the empty quarter in the Kingdom of Saudi Arabia or Oman where there is no availability of proper internet connections that can efficiently allow the transmission of data in real-time. Most of these locations relay on microwave transmission which has its own limitations such as low latency, low bandwidth, and susceptibility to weather conditions. Some countries are solving this challenge by placing 4G mobile towers that can be used for reliable internet, but the costs of those services are still expensive.

The other challenge is the collection of this data requires huge storage capacities especially if real time data has high sampling rates, where information form the embedded sensors are captured every 5ms. Assuming a drilling rig has 20 sensors to capture data from various equipment, where the size of data captured from each sensor per sample is 2bytes, 200 samples will be collected per second from each sensor. This equates to 7.8125 Mb/s or 660 Gb of data per day per rig. If the data was to be collected from the current 650 rigs (Baker Hughes, 2022; Anusha & Umasankar, 2020) currently drilling in the USA, around 420 Tb of storage space would be required per day.

AI integration into existing systems

This challenge was identified by subject matter experts in the survey as a key challenge to the implementation of AI in product design. As the company has existing engineering systems, the implementation of AI within these systems will be difficult as some of those systems are not ready for AI integration. One widely used PLM software among the engineering departments within the company is Teamcenter. Teamcenter was developed by Siemens to help teams produce specifications, analyze reports, create 2D/3D illustrations, and much more in one single location. Unfortunately, Teamcenter is not fully utilized and was heavily modified to suit the requirements of creating engineering drawings, approval processes, and bill of material (BOM) structures. Integrating AI with this modified version of Teamcenter will require extensive programing to adapt it for the use of AI. Therefore, the AI data is not combined or converted to the format necessary for the product design stage. Teamcenter is just one of the existing systems and different engineering departments in different business units use different system, which means that the AI data has to be translated into different formats that can be understood by these systems, increasing the complexity of AI integration across the business.

Another potential roadblock is integrating the AI into predictive maintenance. In this case the result of the equipment analysis has to be fed into the supply chain management system, warehouses, and spare parts availability. After the proper training of the AI, it will be able to predict when certain parts of the products will fail and create a spare parts replenishing schedule that factors in the time to failure, lead time for the spare parts and other environmental factors that might affect the availability and the delivery of the parts. This implementation will bring great benefit especially when lead times of spare parts are very high during the current worldwide disruption in the supply chains. But this implies that the traditional Customer Relationship Management (CRM) software and logistics systems and process will need overhauling to accommodate these AI predictions and autonomously trigger requests for spare parts to cope with the customers' requirements when such parts require replacement.

Data security

The other challenge when it comes to implementation of AI in the design stage of PLM is the security of the transferred data. Security of the data is a prerequisite of a smart design. To ensure that numerous engineers, manufacturing engineers, quality and supply chain receive the required data, huge volumes of data will be transferred over the network. Data that is collected from rig site as described before has to flow safely from the rigs to the datacenters that will process the data. Therefore, secure, consistent, and optimizable security processes will be required. The security systems will have to be equipped with encryption protocols, firewalls, and hacking detection technologies.

Moreover, the data collection devices used on the equipment is usually owned by the operators and consequently, the security of the systems is also a responsibility of the owners who aren't usually property trained to handle information security systems. Industrial communication protocols such as ProfiNet, Profibus DP, EtherCat, and Modbus TCP/IP, which are widely used to communicate between industrial computers and data acquisition modules are unencrypted and thus prone to intrusion and manipulation. If one part of the system is compromised the whole security of the information transfer will be open to security attacks.

The peer-to-peer transfer of industrial data boasts high constraints for the ability to manage and control the data. Any breach in the communication between the peers will ultimately threaten the network as a whole as well as the reliability of the data. New methods are required to securely collect, encrypt, transmit, store, and synchronize the data across distributed storage nodes. The cooperation of the customer and the manufacturer are imperative for the proper implementation for a secure data transfer.

Reliability and trustworthiness of the AI Algorithm

The accuracy and reliability of AI predictions must be very high in safety-critical design applications. In entertainment or e-commerce, an AI accuracy of 90% might be acceptable; in oil and gas equipment design, experts argued that 99%+ accuracy is needed, because lives could be at stake if a design fails. Approximately 70% of respondents expressed only moderate confidence in current AI algorithms' ability to meet such stringent accuracy and reliability requirements. One issue is the proprietary nature of advanced AI algorithms – many cutting-edge AI models are not open source, so a company venturing into this space might have to develop its own algorithms from scratch? These in-house algorithms would initially be weak and require extensive training and tuning to become reliable. The Delphi panel noted that achieving trust in AI would be a time-consuming iterative process: AI recommendations would need to be verified by human experts over many trials. If results are invalid, the algorithms have to be adjusted and retrained, potentially multiple times, until they consistently produce correct outputs? This lack of guaranteed reliability means companies must be prepared for a learning curve and not expect plug-and-play solutions. It also affects human trust: design engineers may be skeptical of AI suggestions until proven otherwise. Building trust will likely involve gradually increasing AI's role as it earns a track record of success. Thus, the challenge is both technical (improving algorithm performance) and cultural (overcoming skepticism). The survey reflected this with about two-thirds agreeing that "AI algorithms need more validation before trusting them with core design tasks." Some even mentioned the need for regulatory standards or certifications for AI in design, similar to how software in aerospace or medical fields is certified for safety – an area for future policy development.

Summary of Challenges with Quantitative Support

To concisely recap, the most frequently cited challenges were:

- Data-related issues: 92% of respondents flagged data availability/quality as a major challenge, and roughly 90% highlighted the immense data volume/storage demands as a barrier.
- Integration and cost: About 87% of respondents agreed that integrating AI into current PLM systems is difficult, and 65% noted high implementation costs (much of which stems from required system upgrades) as a concern.
- Skill gaps: Approximately 80% indicated that a lack of AI-trained personnel in their engineering teams could slow down AI adoption.
- Security and reliability: Around 60% were concerned about data security in AI workflows, and $\sim$ 70% had reservations about the current reliability of AI algorithms for critical design decisions.

These figures demonstrate that while there is enthusiasm for AI's potential, the practical hurdles are significant and broadly acknowledged by industry experts. Any organization planning to implement AI in the design phase must proactively plan to mitigate these challenges – ensuring robust data management strategies, allocating budget for integration, safeguarding data, validating algorithms, and developing talent. Our findings here directly inform to research question four by outlining the conditions under which AI adoption in design will either flourish or struggle within the oil and gas sector.

Conclusion and Limitations

AI implementation has experienced great growth in recent areas as platforms, algorithms, and ways of interaction continue to progress. This research digs into the complicated and intriguing applications of artificial intelligence in the product design cycle in the oil and gas manufacturing business. During the design stage, AI can suggest design improvements and visualize them in a conceptual world. It can also evaluate market requirements to suggest new solutions for the customers in the drilling industry. Embodiment of the design by mapping data from existing operational equipment in the field in a highly accurate manner is another benefit of the AI implementation. Usage for predictive maintenance and supply chain enhancements were also identified in this research where part failure can be predicted and identified based on data collected from IOT devices embedded in the equipment. This data when fed into the AI can result in predictive maintenance schedules and reduce equipment down time as the failure of parts can be predicted ahead of time. Manufacturers can be notified of potential failures and can restock long lead items ahead of time, reducing the customers shutdown periods. From an engineering point of view AI can analysis and decision making when it comes to material selection and BOM population. If the AI was integrated into the supply chain management, it can also analyze supplier performance based on availability of material, lead times, material delivery accuracy and accurate delivery times.

In summary, the study confirms the significant promise of AI in enhancing the design phase of PLM for oil and gas equipment: AI can make design processes more data-driven, connect customer needs more directly into technical specifications, and potentially shorten development cycles while improving product outcomes. These benefits, however, come with caveats as discussed in the challenges section.

Some of the limitations and future research about this topic can be summarized as follows:

- This research is industry-specific and scope-limited. The implementation of the AI and research was done in an oil and gas equipment manufacturing environment and only touches upon the design phase in particular. However, there are two more phases of the PLM that were not thoroughly investigated in this article, the manufacturing and the service phases of PLM. Studying all the phases with respect to AI will give a clearer picture of the complete AI system that encompasses all aspects of PLM.
- The Delphi panel method provided expert consensus but also means the results are somewhat subjective, reflecting the opinions and experiences of the selected experts. A different set of experts or a broader survey might yield additional perspectives.
- AI can be integrated with different technologies and systems for successful implementation. For it to be productive AI depends largely on the quality of the data, the communication systems, and the hardware for data collection. Thus, it is very important to investigate newer communication technologies and their integration with AI to ensure higher reliability of data collection and transfer. Examples of those communication systems may include Starlink, 5G communications among others.

The research already discussed limitations when it comes to standards in industrial communication protocols. Although those protocols are very reliable in the automation industry when used offline, they fail to deliver secure data transfer especially when communication through the internet is required to transfer the data from remote locations to processing centers. Therefore, investigating new industrial communication protocols is imperative for building a solid and secure AI network that is protected against intruders and hackers.

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