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A SURVEY ON PRODUCT MANAGEMENT PRACTICES IN ARTIFICIAL INTELLIGENCE (AI)-POWERED TOOLS AND FRAMEWORKS WITH CURRENT TRENDS AND CHALLENGES

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Abstract: At present, with industries so closely connected globally, upgrading business operations is necessary to stay ahead globally. Industrial enterprises rely on Product Lifecycle Management (PLM) which is a key element for success. By adding AI to PLM procedures, data analyses, machine learning and automation are helping improve how products are managed and the satisfaction of customers. We aim to examine the current use, emerging trends and difficulties in applying AI tools and platforms in PLM. This work shows that using AI in product management allows for better analysis of user behavior, streamlines the design process and supports intelligent automation, all while looking after issues like transparency, fairness and accountability. The report also notes that adding AI from the beginning of PLM to the end makes it easier for companies to innovate sustainably in the products they offer. The goal of this paper is to equip organizations with knowledge to successfully utilize AI in managing the modern demands of product management and compete around the world.

Keywords: Artificial Intelligence (AI), AI Product Manager, Product Lifecycle Management (PLM), Data-Driven Decision Making, Product Development Practices

I. INTRODUCTION

Modern industry moves rapidly, so being able to manage product lifecycles is key to a business' success in many areas. All phases of a product's lifecycle, from start to finish, have their own unique set of unusual problems and options. Because of these difficulties, AI is now changing traditional product management methods[1]. The study explains how AI helps enhance processes, make operations more efficient and stimulate innovation while products are being developed.

As a result of globalization and better technology, organizations are now under more pressure to slash product development time, make operations more efficient and quickly address consumer changes[2]. On the customer side, digital marketplaces allow people to check and compare what is being offered and on the business side, they have to compete with worldwide companies[3]. Also, because fewer companies now manufacture the whole product, it is important for manufacturers and suppliers to partner tightly to keep up and remain agile.

The growth of AI has led to a strong effect on product management. One major change comes from using predictive analytics to direct how products are built. AI tools review a large amount of data, both organized and unorganized, to predict trends in the market, guess customer actions and assess the results of various products. As a result, product managers can make decisions using facts, remain aware of possible missteps and plan strategies that respond to local demands[4][5]. Also, NLP and sentiment analysis used with AI allow the company to check and process opinions on social networks, reviews and surveys in real time, turning these into useful improvements and new inventions.

Reliable growth in digital marketing has also been supported by using AI. Facebook and Instagram use AI tools to look at user data and anticipate what people may like to purchase[6]. It increases customer interaction as well as makes sure budgets are used wisely by eliminating ads that don't target potential customers. Computer vision, a main feature of AI [2], is used in many areas such as facial recognition, public security and the imaging of patients.

ML and DL which are parts of AI, go on to shape technology by allowing systems to learn and change by themselves. Thanks to their use in product management, companies can now build intelligent products that understand and respond to users as well as changes in the market[7][8]. These technologies update product tools and also determine how product managers should handle their jobs.

The transformative effects possible with AI in PLM can be reached only when we face the obstacles it creates, especially in relation to data, explaining models, cohesive integration and ethical questions[9][10]. AI and PLM working together in organizations demonstrates the need to think differently about how products are imagined, made and delivered during today's digital upheaval. The goal of this survey is to give a thorough look at AI-powered product management today, note the trends happening now and identify main obstacles to guide future decisions and research.

A. Organization of the paper

The paper is organized as follows: Section II provide a fundamental of AI in product management, Section III discuss the current trends of PLM, Section IV and V provide future trends and challenges of PLM. Section VI discuss the literature survey of PLM in AI.

II. FUNDAMENTALS OF AI IN PRODUCT MANAGEMENT

IT-based PLM and product data management (PDM) are key ideas in the product development process. PDM has historically evolved and been improved upon by PLM. Thus, PLM's ideas are derived from PDM. First and foremost, Understanding the special duties of the AI product manager is crucial. As AI isn't always suitable in every case, a PM's main duty is to comprehend the most important business issues that AI can resolve[11]. The

second crucial reasonability of AI PM is determining and ranking the appropriate group of issues[12]. Next, create a plan for the necessary stages and a vision approach. Finally, AI PM is in charge of ensuring that it occurs in accordance with the chosen course of action. AI Depending on their line of work, product management may take several forms. Table 1 lists the different kinds of product managers and their responsibilities.

TABLE I. TYPES OF AI PRODUCT MANAGERS

Type	Job duties
Product	works on AI-enhanced products including self-driving cars, online search, and AI ads
Platform	Working on infrastructure and developer tools to create AI
Research	works on research and collaborates with AI researchers to produce research findings. In more prestigious firms, when the whole department is focused on research, they are usually product managers.
Responsible AI	Focus on building AI responsibly

A. Phases of Ai Lifecycle

Every product manager must decide what the intended result is, how it will be delivered, and how the product will be utilized before beginning the construction process. Every time, a new procedure must be started, which is costly and an investment. Therefore, in the first stages, AI product managers have to have access to the same rapid innovation tools used by design specialists, such as wireframes, user surveys, and (UX) mockups. Framing the opportunity or issue that the product solves is crucial. ML can address several types of issues in their ranking suggestion, such as.

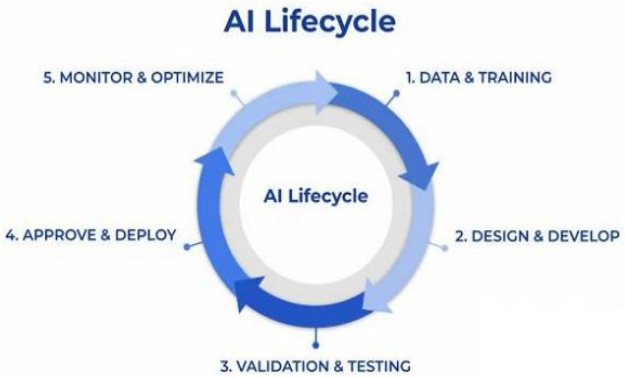

Fig. 1. Lifecycle of AI phases.

Training and data are the first steps in the AI lifecycle. To train the ML algorithms covered above, data is required. Following training, the design and development stages address product creation in accordance with the recommended result of the taught model. Testing and validation are necessary before deployment may be approved. Lastly, as seen in figure 1, AI product managers must keep an eye on optimization to make sure that things continue to evolve even after it is developed and deployed in the open. Therefore, it is crucial to regularly check the system's quality.

B. Responsibilities of AI Product Manager

Given the immense capability of AI, creating such products entails tremendous responsibilities. In medicine, for instance, the Hippocratic vows declare, "First, do no harm." [13][14]. Furthermore, consumers and customers should not be harmed as a starting point by AI practitioners. In other words, AI may have unexpected repercussions if it is not well planned and optimized.

- **Ethical:** More data makes AI better, but it also contains societal and human biases. For instance, facial recognition software is unable to identify faces with darker skin tones. Unknowingly, AI suggests low-paying professions to women and high-paying employment to males. Some important areas of AI's duty are listed below. Product managers for AI must ensure that AI is impartial and fair in order for it to be developed inclusively and ethically.
- **Private and Secure:** As AI is developed, protecting people's privacy is crucial to preventing assaults. There are several fascinating techniques to fool AI. A little amount of picture alteration, for instance, may totally destroy the algorithm used in image recognition. Therefore, it is essential to consider the drawbacks while developing AI[15].
- **Transparent:** In order for AI to be transparent, it must be able to comprehend its motivations and the reasons behind its judgements. This is particularly crucial in situations when the use case has a significant influence on people's lives. Because AI has to be responsible, it needs to be subject to human monitoring, validation, and checks & balances.
- **Reliable:** AI should be dependable in order to maintain good performance over time and prevent model deterioration. It ought to identify problems with the data. That is why it is so important to watch this pipeline up there.

III. CURRENT TREND OF PRODUCT LIFECYCLE MANAGEMENT (PLM)

PLM was first proposed to illustrate how a product develops in the free market, with distinct stages for promotion, maturity, as well as decline. In the field of production engineering, PLM evolved progressively after concurrent engineering was introduced in the 1980s. Among the new PLM process divisions that emerged from it are market analysis, process development, product design, manufacturing, distribution, use, post-purchase service, and recycling. The manufacturing paradigm is always evolving, therefore, various academics have diverse perspectives on PLM[16].

In a prior study, the authors separated the PLM into nine phases based on data gathering, including product idea, design, procurement of raw materials, manufacture, transportation, sale, use, after-sale service, and recycling/disposal[17][18]. In order to categories the techniques and goals of AI technology in distinct phases, this study explicitly divides AI into three stages: product design, product production, and product service. Figure 2 illustrates how each step is further separated into sub-stages.

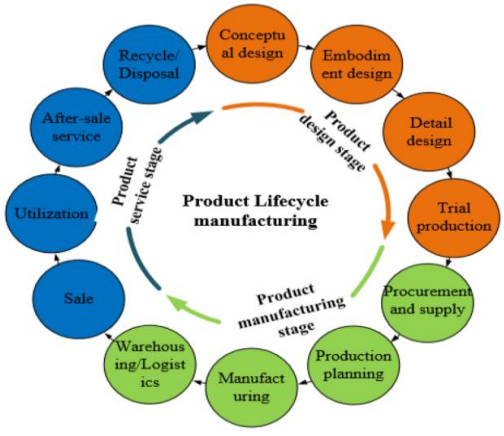

Fig. 2. Continents of PLM

A. Current developing trends of PLM

The same framework is used for all trends in order to study and assess the current IT trends:

1) Definition and function of PLM

The development of PLM originally coincided with the rise in popularity of auxiliary design and production technologies including SCM, PDM, CAD, and CAE[19][20]. The evolution of PLM began with the tool period and continued with the integrated application and collaborative platform eras. Continuous development, adaptation, and integration of new technologies and tools in response to dynamic shifts in business, management, and production methods ultimately resulted in the present PLM form.

2) Information integration framework of PLM

A comprehensive information architecture that integrates disparate data, information, and technologies is essential to the practical use of PLM. PLM information integration calls on a variety of technologies, including web service connections, data mapping, knowledge and semantic integration, general theories and techniques, and particular technologies related to information interaction. The PLM integration framework's needs and components are progressively improved by the new production modes. Nevertheless, because to the wide range of PLM, the majority of current frameworks are designed for a specific application situation, which hinders their ability to be used universally.

3) Modeling methods and tools in PLM

PLM oversees goods data gathered about design, production, and servicing throughout the course of a product's lifespan. To integrate many PLM components, a variety of data models, information models, as well as workflow models were developed[21]. The majority of PLM models are implemented locally to improve the efficacy of a particular PLM stage rather than the PLM process as a whole. For instance, by coordinating choices made by several designers using various design tools, the design management model helps to derive design solutions. BOM-based product modelling works well for monitoring execution timelines and creating more precise production plans.

4) Optimization and evaluation in PLM

The PLM framework has included a number of optimization and evaluation methods. In the design phase, assessment methods such as the Kano Model, Effects Analysis, Analytical Hierarchy Process (AHP), as well as Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) are often used. Typical assessment criteria include environmental friendliness, development cycle, efficiency, and beauty. popular assessment indicators for the production stage include make span, cost, energy consumption, and resource utilization; different meta-heuristic algorithms reflect popular optimization techniques[22].

5) Data management in PLM

The extensive use of embedded technologies, such as RFID tags and advanced sensors, in the production and service phases has led to a rapid growth of PLM data. Much work is being put into creating new methods for PLM data modelling, synchronization, integration, transformation, and mining[23][24]. As new technologies like as digital twins and the Industrial Internet become more widely used, PLM data will continue to increase in quantity and variety.

B. New requirements of PLM

PLM is becoming subject to increased demands as a result of the need for greater product quality, inventiveness, and cost-effectiveness[25].

- Manufacturers must alter their processes in order to reduce the life cycle of a product, particularly the product design and production stages' cycling velocity, in order to react swiftly to changes in the market.
- Manufacturers need to develop more responsive, flexible, and modularized manufacturing, design, as well as service processes in response to the growing market demands for personalized and customized goods.
- In order to create, produce, and handle customized goods on a global scale, manufacturers need to interact with the appropriate parties, pool resources, and establish sustainable manufacturing networks.
- Manufacturers must improve the intelligence of their manufacturing systems and processes due to the increased competition for lower costs, better quality, and shorter lead times. This raises the bar for equipment intelligence and process automation.
- A vast amount of industrial big data has emerged, necessitating that manufacturers handle, integrate, mine, and classify a variety of high-dimensional, unlabeled, unstructured, and non-standardized data.

The authors discover from the aforementioned debate that the PLM's emphasis is progressively changing from offline manufacturing to online collaboration, goods to services, and from informatization to intellectualization. AI is crucial to the new information technologies that academics and industry have worked so hard to develop, in order to fulfil the evolving needs for PLM.

IV. The Future Of Product Management: Emerging Technologies

In the future, AI-powered automation will lead the way in product management. By using ML and AI algorithms to automate repetitive and redundant tasks, It will make it possible to manage the product life cycle and streamline procedures and workflows from marketing, customer service, product testing, and research[26][27].

The procedure is streamlined via automation, cuts down on marketing time, and frees up more time for teams to work on important projects. In the field of product management, augmented reality interfaces will revolutionize technological innovation by improving user experiences as well as product visualizations. The latest trends and technology in product management are shown in Figure 3.

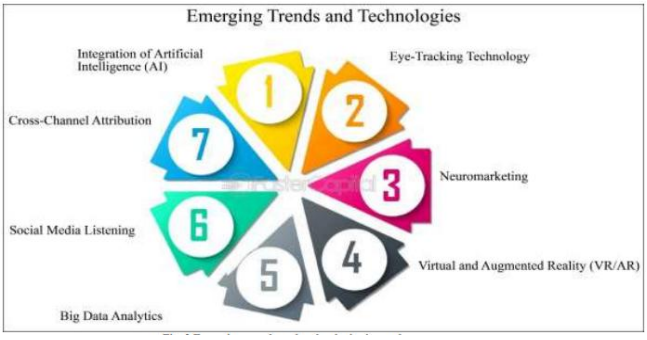

Fig. 3. Emerging trends and technologies in product management

- **Integration of Artificial Intelligence (AI):** The increasing incorporation of AI across various industries

is a significant trend. AI is the development of computer systems that are capable of learning, problem-solving, and decision-making—tasks that often call for human intelligence. This integration spans applications from automating routine processes and enhancing data analysis to powering personalized customer experiences and driving innovation in fields like healthcare, finance, and manufacturing.

- **Eye-Tracking Technology:** The technology tracks and analyses where someone is looking with their eyes. Following how much and what people look at, as well as their order of gaze, can tell us about their level of attention, engagement and mental functioning. Usability testing webpages and software, studying what consumers do when viewing ads, assisting people with disabilities and supporting activities in games and virtual reality are all ways eye-tracking is utilized.
- **Neuromarketing:** In neuromarketing, we use neuroscience techniques to study consumer reactions to marketing activities. To better understand what consumers like subconsciously and how quickly they decide, marketers measure the brain, physiology and eye movements of people. This understanding can guide marketers to improve the ways they advertise, make products and brand their company.
- **Virtual and Augmented Reality (VR/AR):** Virtual Reality programs involve users in life-like fictional worlds designed by computers which they can control with headsets and input devices. Augmented reality, which may be seen with a smartphone, tablet, or AR glasses, overlays the actual environment with digital data and virtual objects. Entertainment, education, training, design and collaboration for remote teams are being transformed using VR and AR.
- **Big Data Analytics:** The exponential increase in data volume, velocity, and diversity (often referred to as "Big Data") necessitates sophisticated analytical techniques to extract meaningful insights. Big Data analytics involves using advanced statistical and computational methods to identify patterns, trends, and correlations within large datasets[28]. This enables organizations to make more informed decisions, predict future outcomes, personalize offerings, and gain a competitive advantage across numerous industries.
- **Social Media Listening:** This entails keeping an eye on and evaluating discussions and patterns on social media sites. By tracking mentions of brands, products, competitors, and relevant keywords, organizations can gain valuable insights into public opinion, customer sentiment, emerging trends, and potential issues. Social media listening helps in understanding customer needs, identifying influencers, managing brand reputation, and informing marketing strategies.
- **Cross-Channel Attribution:** In today's multi-channel marketing landscape, understanding which touchpoints contribute to a customer's conversion journey is crucial. The purpose of cross-channel attribution is to comprehend which marketing channels (such as email, social media, paid ads and the website) influence how customers interact and end up making a purchase. Marketers can improve how they use their resources and strategies by correctly assigning value to each channel.

V. Challenges In AI-Powered Product Management

AI is now deeply connected to modern software and managing the tools and frameworks it uses often reveals unique challenges and chances. This transformation is supported by managing data products which involves finding a balance between invention, rules and how people use the results[29]. AI offers many ways to boost a business, but it also requires data product managers to handle new complexities. Managing well requires knowledge about technology, along with planning, knowing laws and continuously changing to match trends.

There are several hurdles within product management.:

- **Complexity of Data Ecosystems:** A major difficulty in using AI for product management is the complexity of current data systems. It is normal for an organization to work with various data sources that aren't the same in how they are organized or formatted. Putting all the different aspects of security into one system is not easy and takes time[30]. Because it is complicated, this process can delay making products, result in inconsistencies when the data is viewed and raise the possibility of errors that can impact the performance of AI models and data products.
- **Implementing Effective Data Governance:** Proper data governance guarantees all AI systems have the same standards, are safe and everyone can be held accountable for their use [31]. It is important for data product managers to develop frameworks that control the way data is obtained, saved and used throughout the organization. Thanks to these frameworks, managing lots of data is simpler and encourages transparency, reliability and compliance. Without proper leaders, managing data assets can become confusing which may invite inefficiencies and lawsuits.
- **Maintaining High Data Quality Standards:** The success of AI tools depends on having quality data. It is up to data product managers to identify and set standards for proper data quality in the organization. You should design solutions for cleaning, verifying and tracking your data. Flaws in data quality can greatly negatively impact the accuracy and reliability of AI which underlines the need for businesses to make improving data quality a fundamental part of their product building process.
- **Navigating Regulatory Compliance:** Data privacy rules like GDPR and CCPA now make it much more challenging for companies using AI to achieve compliance. A data product manager should make sure that all their data practices follow new legal trends and protect private and sensitive information. This also involves following new regulations and including compliance steps throughout the entire use of data.
- **Adapting to Rapid Technological Change:** Progress in AI, machine learning and cloud infrastructure is happening at an endless pace. Data product managers should quickly respond to new technologies that might improve their product or alter how things are done[32]. Occasionally updating and upgrading tools and frameworks may burden the team and call for wise strategies to maintain the company's overall development goals.
- **Commitment to Continuous Learning:** Given the fast nature of development in our field, education becomes essential. Managers in data products should continue their education by going to conferences, relying on the insights of top experts and becoming members of related communities. Because of their commitment, they can pick out and integrate the latest advancements in their workflows, enabling their products to stay on the leading edge.

- **Addressing Skills Gaps and Organizational Readiness:** Often, AI-based technologies need people who have specific skills that aren't always available in present staff. Assessing what the organization can do and improving capabilities by training or hiring new staff or outsourcing are tasks for a data product manager[33]. Most promising AI ventures will struggle or not succeed if the team lacks the needed skills.
- **Managing Innovation-Driven Uncertainty:** As AI brings new inventions, it also creates doubts about how to invest, what the ROI will look like and the influence on the company's workings. It is necessary for data product managers to review how new technologies might impact the company while still having the flexibility to make quick shifts. It is very important that AI-powered products grow sustainably by finding balance between innovation and stability.

VI. Literature Of Review

This literature review highlights advancements in sustainable PLM, agile integration, digital tools, blockchain adoption, and software product management frameworks, addressing efficiency, transparency, and technological innovation across product life cycles.

Abdul-Azeez et al., (2024) the role of easy-to-follow supply chains and ethical supply partners, so sustainability remains important at all points in a product's life. Barriers to sustainable PLCM which involve finding the right balance between finances and environment and dealing with strict regulations, are talked about as well. All in all, the review finds that the main factors for success are stakeholder involvement, use of current technology and an ongoing commitment to sustainable practices by the company. Such factors are necessary for businesses trying to be leaders in sustainability and keep their edge in a market focused on the environment. Topics: Sustainability, Managing Products over a Lifetime, Fine Practices, New Innovations, Eco Design, Circular Economy, Sustainable Production, Transparent Supply Chains, Lifespan Assessment, Protecting the Environment[34].

Attah et al., (2024) Using digital tools for keeping track of projects, communicating and looking at performance data is looked at as a way to make things more efficient and easier to decide. After analysis, the paper introduces a complete system for technology-led project management, emphasizing ways to quickly finish products and secure future market expansion. It provides guidance to businesses wanting to improve how they manage projects in the digital era by bringing together top practices from several industries[35].

Ibeh et al., (2024) proves that following agile ideas while reaching PLM targets helps integrate digital systems. By blending theory and practice, we hope to lead organizations in using agile ideas to develop their products in a fast-changing digitized environment. With this review, both academia and industry specialists gain insight into how simplified, agile approaches to workstreams can be used together with PLM to increase digital technology integration[36] It was suggested by Xin, Ojanen and Wang, (2023) that waste management and recycling businesses may benefit from one another's knowledge when they work together. To support one another's activities, businesses and scientific research institutions should work together more closely. This study reviews previous research and conducts empirical interviews with four recycling and waste management organizations in Finland to investigate the knowledge management practices in the end-of-life phase of product-service systems.[37].

Hayat and Winkler, (2022) determined that the majority of PLMs now in use lack certain necessary characteristics; as a result, industries often combine several software programs to create a complete PLM system. Nevertheless, this approach lowers the system's overall efficiency. Therefore, this research highlights that in order to address PLM difficulties and their effects on production sectors, it is imperative that a new technology, such as blockchain, be used[38].

Springer, Miler and Wróbel, (2023) a collection of 39 fixes for the top 5 issues that product managers face on the job. Additionally, recommendations for these issues were created based on the solutions that were found and the outcomes of the focus groups' conversations with seasoned experts. These recommendations may be used by product managers & other members of the product development team to create their own strategies for improving software engineering practices and addressing software product management problems. Ultimately, The principles and solutions provided will be combined with a list of problems identified in previous studies to build a Software Product Management Guide, a framework now being developed as part of larger study, to assist product development teams in improving software engineering methods[39].

Table 1 summarizes recent studies addressing sustainability, digital transformation, agile PLM, knowledge management, blockchain integration, and software product management. Key challenges include adoption barriers, cost-environment trade-offs, fragmented collaboration, and the need for scalable, empirically validated frameworks across industries.

TABLE II. Summary on Product Management Practices in AI-Powered Tools and Frameworks

Reference	Focus area	Key Findings	Challenges	Limitations / Future Gaps
Abdul-Azeez et al., (2024)	Supply chain transparency and sustainable PLCM	Importance of ethical sourcing and sustainability throughout the product life cycle; success factors include stakeholder engagement, innovation, and organizational commitment.	Balancing cost vs. environmental benefits; regulatory complexities.	Need for deeper exploration into scalable sustainable PLCM models across different industries.
Attah et al., (2024)	Technology-driven project management	Integration of digital tools enhances project efficiency and decision-making; provides a framework for both short-term success and long-term growth.	Managing technology adoption and change resistance; ensuring interoperability.	Further studies needed on sector-specific digital implementation and ROI.
Ibeh et al., (2024)	Agile methodology in PLM	Aligning agile with PLM can optimize product development and digital technology integration.	Difficulty aligning agile with traditional PLM frameworks.	Empirical validation needed across various organizational contexts.
Xin, Ojanen, and Wang (2023)	In systems that use end-of-life products and services,	Advocates for neutral agreements and collaboration with scientific institutions to improve recycling and waste management knowledge exchange.	Fragmented collaboration; insufficient data sharing practices.	Future work should focus on global scalability and standardization of practices.

	knowledge management			
Hayat and Winkler (2022)	Blockchain for PLM integration	Most PLMs are incomplete; blockchain offers a novel solution for system inefficiencies.	Integration complexity; blockchain adoption barriers.	Real-world implementation cases are limited and require further investigation.
Springer, Miler, and Wróbel (2023)	Challenges in managing software products	Developed 39 solutions with guidelines to address common SPM issues; proposed framework for improving software engineering.	Lack of standardized solutions; varying team dynamics.	Framework under construction; requires testing and refinement across diverse software environments.

VII. Conclusion And Future Scope

AI has significantly transformed product management by automating key processes, reducing reliance on intuition, and enabling data-driven decision-making. These advancements have contributed to improved product quality, reduced development timelines, and more informed strategic planning. Through capabilities such as market trend analysis and customer behavior modeling, AI empowers product managers to create offerings that better align with consumer needs and preferences. However, there are obstacles to overcome when integrating AI into product management. Responsible AI deployment requires addressing issues including algorithmic bias, data privacy, ethical considerations, and the need for openness. Organizations can mitigate these risks by adopting robust governance frameworks that promote fairness, accountability, and trustworthiness in AI systems. When implemented strategically, AI enables organizations to enhance innovation, improve customer experience, and maintain competitiveness in an increasingly dynamic digital marketplace.

Future opportunities will offer even more innovative product experiences that leverage AI to provide personalization and analytics. The evolution of generative AI, enabling autonomous decision-making will add further dimension to the product life cycle. Research and advancements will lead to smarter, adaptive, adaptive, and moral applications of AI systems across a range of goods and industries.

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