

AN EXPLORATION OF THE APPLICATIONS, CHALLENGES, AND SUCCESS FACTORS IN AI-DRIVEN PRODUCT DEVELOPMENT AND MANAGEMENT

Aron WITKOWSKI^{a)}, Andrzej WODECKI^{b)}

Warsaw University of Technology, Faculty of Management, POLAND

^{a)} e-mail: aron.witkowski.dokt@pw.edu.pl, ORCID: 0000-0003-4126-0274

^{b)} e-mail: andrzej.wodecki@pw.edu.pl, ORCID: 0000-0002-9077-3191

Abstract: While extensive research studies exist on the influence of AI solutions on organizations as a whole, there is a paucity of comprehensive studies examining the adoption of these solutions in product development and subsequent management processes. This article presents an exploratory investigation of the applications, challenges, and determinants of success associated with artificial intelligence (AI) solutions employed in the product development and management processes. To this end, a qualitative thematic analysis is conducted based on twelve in-depth interviews with experts proficient in AI engineering and product management, representing twelve distinct organizations within the Polish IT sector. This article offers insights into four potential applications and expounds on various factors impacting the challenges and success of deployed AI solutions, generating two additional emergent themes. This article delineates practical implications for organizations and product managers and proposes intriguing directions for future research exploring topical areas of study.

Keywords: artificial intelligence, machine learning, product management, AI-driven development, data-driven development, new product development.

JEL Classification: O31, O32, O33, M15, M30.

1 Introduction

Numerous enterprises across the globe employ data and artificial intelligence (AI) algorithms to enhance their product offerings and maintain a competitive edge. These techniques yield valuable insights into the aspects requiring improvement, modifications in product design, and even optimal store locations to boost sales. According to Puntoni, et al. (2021), AI is defined “as an ecosystem comprising three fundamental elements—data collection and storage, statistical and computational techniques, and output systems—that enable products and services to perform tasks typically understood as requiring intelligence and autonomous decision making on behalf of humans.” As data constitute the core of AI-based systems, multiple challenges arise concerning its quality, procurement, and utilization, among other aspects (Prem, 2019). Furthermore, AI algorithms present their own set of issues, such as explainability and trustworthiness.

Despite these problems, companies are adopting data and AI solutions during product development and management. Interestingly, some studies indicate a

separation between AI-driven development and data-driven development. According to Bosch, Olsson and Crnkovic (2018), data-driven development is an “approach where development teams receive a quantitative target, i.e. an outcome, to realize and are asked to experiment with different solutions to improve the metric,” and AI-driven development is an approach where “company has a large data set available and use artificial intelligence techniques such as machine learning and deep learning to create components that act based on input data and that learn from previous actions.” Based on these definitions, data-driven development approach is commonly used by companies when there is a metric of some product feature that needs to be improved, and the team mainly does this by running A/B or MAB test and is not likely to be used for high-impact business choices such as new product development. On the other hand, the AI-driven development approach is mostly used by companies in situations where it is important to minimize prediction errors and where there are many different alternatives for a solution, so the difficulty, cost, or time to process them manually is too high (Bosch, Olsson and Crnkovic, 2018).

According to Hughes and Chafin (1996), “strategic product planning, initiation and market introduction of product innovations, alongside with maintenance and improvement of existing products, are the central tasks of product management.” Most of the research studies related to product management are focused on New Product Development (NPD), which would coincide with the above definition. There have been many different approaches to dividing NPD into different phases, while most focus on distinguishing six phases: product ideation, business analysis and concept generation, product design and development, product testing and validation, product launch, and product improvement (post-commercialization phase). Based on the above definitions, the concept of AI-driven product development and management is the use of AI solutions in each phase of the product lifecycle from ideation to product launch and its subsequent management.

In our research, through a set of semi-structured interviews, we aim to explore the concept of companies' familiarity with the introduction of AI solutions in the product development and management process, and the challenges faced by companies that would like to introduce such solutions in the aforementioned process and the success factors that demonstrate that such solutions have been introduced in an effective manner. To achieve this goal, the following research questions (RQs) were formulated:

RQ1. How are companies currently using AI solutions in product development and management process and what are other desirable use cases?

RQ2. What are the challenges faced by companies looking to implement AI solutions in product development and management process, and how can the success of these implementations be determined?

The paper is structured as follows: Section 2 provides a description theoretical background of the study. Section 3 shows the research approach used. Section 4 presents the research results, while Section 5 discusses the implications for organizations and researchers. Section 6 summarizes the paper, indicating its limitations and future research directions.

2 Theoretical background

The following subsections discuss the most common applications, challenges, and success factors in using

AI solutions in the product development and management process, which has been examined in existing literature.

2.1 Key AI methods applied to product development and management

Essential AI methods and techniques are employed in the product development and management process, encompassing areas such as prediction, optimization, automation, textual analysis (Natural Language Processing domain), and visual analysis (Computer Vision domain). Diverse methods are utilized contingent on the phase of product development or subsequent management. In the product ideation phase, Natural Language Processing methods are predominant, particularly knowledge extraction, sentiment analysis, and conversational AI. Knowledge extraction methods can be used to extract product ideas from various online sources (Luo, Huang and Zhu, 2019; Zhang, et al., 2021), sentiment analysis to assess the positivity or negativity of product reviews (Aguwa, Olya and Monplaisir, 2017; Giannakis, et al., 2022; Symeonidis, Peikos and Arampatzis, 2022), and conversational AI in the form of chatbots to interview customers to extract product ideas directly from them (Chen, Le and Florence, 2021; Eren, 2021). In the design and development phase, the aforementioned methods can also be applied to source design ideas; however, in this phase, Computer Vision and techniques related to autonomous systems and robotics play a significant role, especially for physical products, by assisting with product manufacturing (Tubadji, Huang and Webber, 2021; Johnson, et al., 2022). Vision methods are particularly instrumental in product quality management and testing (Chen and Wang, 2018; Jain, Meenu and Sardana, 2020; Liao, et al., 2021; Zhao, et al., 2022), including anomaly detection (Langone, Cuzzocrea and Skantzios, 2020; Garg, et al., 2021).

Various AI solutions are employed in finished product management, encompassing prescriptive analytics (Viswanandhne, et al., 2019), competitor or customer analysis (Luoma, et al., 2017; Ballestar, Grau-Carles and Sainz, 2019), churn prediction (Pustokhina, et al., 2021), personalization (Byrd and Darrow, 2021), store layout (Huang, Bergman and Gopal, 2019; Lee and

Shin, 2020), demand and sales forecasting (Koulouri-otis and Mantas, 2012; Atsalakis, 2014; Jin and Shin, 2020), or choice modeling (Liebe and Meyerhoff, 2021). Although in a number of articles various artificial intelligence solutions have been used at different stages of the product development and management process, the plethora of solutions means that companies may not be aware of some of the possible AI solutions, and therefore may not incorporate these solutions into the process.

2.2 Challenges with the data and algorithms

In both data-driven and AI-driven product development, data serve as the central component. To construct and enhance new products, organizations must manage vast quantities of data and possess the appropriate infrastructure for this task (Bosch, Olsson and Crnkovic, 2018). Based on interviews conducted by Figalist, et al. (2020), a mere 9% of respondents indicated that the effort required to establish infrastructure for software analytics and AI-based business intelligence is relatively low or very low. In contrast, over 50% reported that it is high (37%) or very high (14%). The endeavor to create the right infrastructure presents challenges not only from a financial standpoint but also due to technical complexities (Figalist, et al., 2020). Data are hard to access and difficult to process (Patil and Mason, 2015). AI solutions can manage both structured and unstructured data; however, preprocessing is a prerequisite, and this process entails data cleaning, transformation, and selection, each of which can rapidly become multifaceted and intricate.

The literature also identifies data quality as a significant challenge in new product development (Cubric, 2020; Figalist, et al., 2020; Paschen, Pitt and Kietzmann, 2020). Data quantity seldom corresponds with quality—organizations gather data from various sources, complicating the maintenance of high-quality standards. Furthermore, the data may be incomplete, defective, or biased, leading to suboptimal AI algorithm performance and ultimately, undesirable products.

Privacy and security constitute another considerable concern (Paschen, Pitt and Kietzmann, 2020). Individuals are more aware of their privacy than ever before

and expect transparent communication from companies regarding data collection, processing, purpose, and security measures. In particular, the intricacies of AI algorithms' data handling are challenging to elucidate, even for the scientists who develop these algorithms, which further complicates obtaining user consent.

2.3 Value-risk trade-off in a world of data and AI

The longstanding question of generating value from new products has assumed a novel dimension with data and AI. Mishra and Pani (2020) posit that there are two approaches to deriving value from new technology: exploiting, which involves extending the current capabilities of the technology, and exploring, which entails discovering new alternatives. This assertion is equally applicable to AI solutions. Companies aspire to utilize AI in product development to foster innovation, optimize manufacturing processes, enhance efficiency, and augment complexity and knowledge management (Prem, 2019).

Nonetheless, organizations contemplating the adoption of AI frequently fail to implement it (Mishra and Pani, 2020). One contributing factor is the insufficient knowledge on how to extract value. Another factor is risk aversion, as there is a general inclination to mitigate risk rather than to maximize the value (Desouza, Dawson and Chenok, 2020). When presented with opportunities exhibiting a low risk and low value or high risk and high value, companies often explore partnerships, not only with other enterprises but also with academic institutions (Magistretti, Dell'Era and Messeni Petruzzelli, 2019; Mishra and Pani, 2020) to develop AI-based solutions. However, some studies suggest that such collaborations are occasionally underutilized by companies due to the gap between practitioners and academia, resulting in a dearth of direct benefits for the organization (Mishra and Pani, 2020).

For low-risk and high-value situations, companies tend to develop products internally (Desouza, Dawson and Chenok, 2020). The principal challenge in managing data-driven or AI products, stemming from prior data issues, is the initial cost and time (Prem, 2019; Figalist, et al., 2020; Paschen, Pitt and Kietzmann, 2020). Priorities are redirected to other subjects and products, causing insufficient resources, and without resources,

R&D departments cannot demonstrate a value. Various studies indicate that the most effective strategy to disrupt this vicious cycle is to construct a low-cost minimum viable product (MVP) internally (Figalist, et al., 2020; Desouza, Dawson and Chenok, 2020) and then determine subsequent steps. Research also highlights the ease with which R&D departments can succumb to the efficiency trap rather than concentrating on effectiveness, where effectiveness is defined as “the amount of customer value created per unit of R&D resources” (Bosch, 2019). In the final case of high-risk and low-value solutions, companies opt to outsource the work (Desouza, Dawson and Chenok, 2020; Cricelli, Grimaldi and Vermicelli, 2022).

2.4 Intuition-based decisions versus AI-driven decisions

The aforementioned issues with data quality, algorithms, and ultimately, products lead stakeholders to increasingly doubt the results and profitability of employing AI data and algorithms in product development (Figalist, et al., 2020). Utilizing data and AI to create a product can be considered an IT project, and statistics reveal that IT projects are generally more complex and prone to failure than other types of projects (Mishra and Pani, 2020). This presents an additional factor that could negatively influence executives’ decision to initiate product development using these techniques.

Within product development teams, a prevalent discord is observed, primarily between managers and software developers. Managers are often skeptical upon witnessing initial results without discerning the benefits or possess limited general AI knowledge, leading to premature resistance and rejection of the concept. This knowledge deficit also results in unrealistic expectations for AI products (Figalist, et al., 2020), concerning not only product functionality and cost but also time-to-market. Frequently, managerial ignorance causes unreasonably short timeframes to be imposed for developing the appropriate solution. A related issue is the challenge of knowledge transfer—R&D departments must educate managers on product functionality, who, in turn, must understand the product sufficiently to defend its value to higher management. Failure in this regard may not indicate

a worthless product but rather an inadequate understanding of complex AI methods by the manager to grasp and defend the solution (Figalist, et al., 2020).

In many organizations, executives and managers rely on business intuition. When data are available, this reliance is unnecessary because data present facts—product perception, purchase locations, associated products, etc. However, executives and managers sometimes prefer their opinions, even when data suggest otherwise. Moreover, their beliefs are so deeply ingrained that they attempt to interpret data in a manner consistent with their preconceptions, rather than accepting objective reality (Bosch, 2019; Santana and Díaz-Fernández, 2022; Zirar, 2023). This issue is closely tied to trust—namely, the extent to which we can trust data. If factual data cannot be trusted, how can we have faith in AI algorithms when even the software developers who create them struggle to explain their functionality?

2.5 Lack of proper methodology

As commercial AI solutions are still in relatively early development stages, a general set of guidelines for AI-driven product development and management is lacking, which could be adapted on a product- or sector-specific basis. Bosch, Olsson and Crnkovic (2018) note that AI-driven development “is still in its infancy in many of the companies we studied we foresee significant work in the area of defining systematic and repeatable methods for creating, evolving, and maintaining systems using AI techniques.” One of the solutions could be implementing and maintaining machine learning models based on a flywheel loop. Applying the flywheel to product strategy (Gurkan and de Véricourt, 2022) aids product managers in building less prescriptive product roadmaps and making more data-driven (or AI-driven) decisions. If AI-driven product development and management involves using AI solutions in each phase from ideation to implementation and optimization, a product AI strategic flywheel or AI solutions closing the product strategic flywheel loop could create such a model. The product managers, along with their team, would adapt this generic model to the company’s products. According to Bosch (2019) and Cubric (2020), future research on AI

in business should focus on methodology improvements, including better evaluation methods and multi-disciplinary approaches. To fully realize AI's potential in product development and management, organizations must develop strategies that effectively address these challenges.

2.6 Impact of AI introduction on the product's success

When evaluating the success of a product, two pertinent questions arise: what determines product success? (i.e., the factors contributing to product success) and how success is measured? General product success factors identified in the literature include innovative value, strategic approach and vision, a high-quality and structured new product development process, market research, customer-centricity, and retention of qualified employees along with necessary resources and infrastructure (Soltani-Fesaghandis and Pooya, 2018). According to Duan, Edwards and Dwivedi (2019), extensive research has been conducted on factors influencing the use, impact, success, and failure of information systems, yet there are limited research studies on identifying critical success factors for AI and its impact in the Big Data era.

In terms of success factors for AI implementation in companies, McKinsey (2021) distinguished several categories differentiating AI high performers (those attributing at least 20% of EBIT to AI solutions) from other companies. Baseline factors and user enablement-related factors encompass design thinking in AI solution development, a clear governance model for AI solutions, AI-related staff skill development programs, and explaining model basics to users or providing hands-on training for non-technical staff. More advanced factors associated with data, tools, and technology include a single, accessible data dictionary across the organization, aligned and scalable internal processes related to data use and labeling, and a focus on regular refresh, explainability, and reusability of AI models and engaging third-party companies for testing and validation of AI models.

Companies employ various approaches to measure the success of AI implementation in product development and management processes. Benefits can be classified as intangible (difficult to measure) or tangible (directly

translatable to numerical value). Intangible benefits include culture change (AI drives product innovation culture), competitive advantage (delivering significant product value change), and the halo effect (attracting new customers due to AI-driven processes). Tangible benefits primarily encompass cost reduction (and/or avoidance), revenue increase, customer satisfaction (measured through CSAT and NPS metrics), risk mitigation, and compliance (through avoided costs) (Burgess, 2018). According to McKinsey (2021), 69% of respondents surveyed in 2020 who had implemented AI solutions in their company reported a cost decrease following AI implementation in product and/or service development, with a third of respondents indicating a decrease greater than 20%. In terms of revenue increase, 70% of respondents reported an increase after introducing AI solutions in product and/or service development, with 40% of the increase exceeding 6%.

3 Research design

In our study, we focused on qualitative, semi-structured interviews with experts in the core fields of AI and product development and management, drawing upon (Flick, 2023). We conducted internet searches using LinkedIn and Google to identify organizations in Poland within the IT sector that emphasized the utilization of AI solutions on an organization-wide scale. In total, 42 such organizations were discovered. Email was employed as a means to solicit volunteers. The criteria were general work experience of at least 5 years, including at least 1 year addressed product management and at least 1 year addressed implementing AI solutions (as a product manager or software developer and similar). Additionally, as an optional requirement, we sought individuals who, in addition to meeting the above criteria, were also involved in research themselves, which aids in better understanding the nature of our study and facilitates the collection and validation of results. Credibility was checked at the beginning of the interview—if the respondent considered the online data to be incorrect, i.e., the company was not involved in the use of AI solutions in the product development and management process or the candidate did not meet the aforementioned criteria, the interview was not continued. Twelve participants who met the criteria volunteered for the study. The selected participants were

based in Poland and represented twelve different organizations within the IT sector. Recruitment concluded when data saturation was achieved, and no new

themes emerged. A summary detailing the profiles of the interviewees can be found in Table 1.

Table 1. Profile of the interviewees
(Source: Own study)

Interview reference	Current position	Years of experience
A1	AI engineer	5 years
A2	Head of Product Development	11 years
A3	Head of R&D / Researcher	10 years
A4	Product Owner / AI Product Line Manager	5 years
A5	VC Founder / Researcher	15 years
A6	Data Science Engineering Manager / Researcher	6 years
A7	Head of AI / Researcher	7 years
A8	VC Investor / Researcher	6 years
A9	CTO / Researcher	9 years
A10	Lead Data Scientist / Researcher	7 years
A11	ML Consultant / Researcher	6 years
A12	Senior Product Manager	8 years

A semi-structured approach was employed to guarantee comprehensive coverage of all research areas. An open-ended questioning style complemented the semi-structured questions, and the interviewer addressed any inquiries seeking clarification. A pilot interview refined the questions to ensure clarity and focus on all aspects related to the applications, challenges, and success factors of implementing AI solutions in the product development and management process.

Feedback from the pilot led to the addition of two further questions. The interview was developed in a format suitable for both in-person and remote use. The interview questions were divided into four sections:

- Section 1, "About you," gathered the necessary demographic information, role description, and experience in product management and AI solutions.
- Section 2, "Implementation of AI solutions," concentrated on current and potential AI solutions in the product development and management process.
- Section 3, "Challenges and success factors," investigated the challenges respondents encountered, the success factors, and methods for measuring success.
- Section 4 solicited any additional comments.

A single independent researcher conducted the semi-structured interviews, typically lasting between 30 and 90 minutes. The interviewer sought clarification to ensure that all interviewees understood and interpreted the questions in the same manner. All data were coded based on a thematic approach (Flick, 2023). Thematic analysis was employed to examine themes within the collected data relevant to the researched areas. Themes were identified by searching for commonalities, relationships, and differences. The data were read and re-read to confirm that the identified themes were accurately captured.

4 Results

The data pertained to three primary research areas of interest, namely applications, challenges, and success factors of AI-driven product development and management processes, with two additional themes emerging from the data. The manner in which data were selected as relevant to the core research areas originated from a content analysis of the themes. The themes of knowledge and responsibilities of the product manager, and treating process improvement as a product, were related to all three core research areas

and were discussed separately as overarching themes. These overarching themes were identified through content analysis and their association with AI-driven product development and management in general. The

overarching themes were discussed first, followed by each of the core research areas and their associated topics. Table 2 summarizes these findings.

Table 2. Applications, challenges, and success factors identified from the interviews
(Source: Own study)

Research area	Factors / examples identified
Applications	Everyday tools that support the work of product managers, which are based on AI solutions, enhancing work efficiency and speed (A4, A8, A10)
	Solutions that relieve the product manager of all tasks not related to their core responsibilities for product development and management (A3, A12)
	An AI guide to the new product development process, which directs product managers on actions to take during specific phases of the process (A4, A6, A11)
	AI tools that aid in making product business decisions (A6, A9)
Challenges	High volume of high-quality data and processing these data to make improved business decisions (A1–A12)
	The approach of people in the organization to the use of AI solutions, primarily unrealistic expectations about what is achievable (A1, A3, A5, A6, A8, A9)
	Security and privacy related to product data, particularly when it involves the use of these data by external companies to develop tools that support the work of the product manager (A1, A4, A5, A7, A8, A11)
	Trust and explainability of the data presented to the product manager (A1, A2, A4, A5, A7, A8, A11)
	Computing power required to implement and maintain models for AI solutions (A9, A11)
	Lack of clear methodology on how to introduce AI solutions in the product development and management process (A1, A11, A12)
Success factors	Appropriate metrics to evaluate how the AI solution has aided the process (e.g., financial or time-based) (A1, A4, A7, A8, A9, A11)
	Ability to accurately assess the business impact and feasibility of the introduced AI solution in advance (A1, A3, A5)
	Team quality and interdepartmental collaboration across the organization (A2, A3, A5, A7, A12)
	One general data dictionary across the organization (A2, A12)

Note: In brackets are presented interview references, from which the factors / examples are derived

4.1 Overarching themes

Two themes appeared to be related to AI-driven product development and management process in general:

- knowledge and responsibilities of a product manager,
- process improvement as a product.

These themes are now examined in relation to the interview data.

Knowledge and responsibilities of a product manager: Most respondents (A1, A2, A4, A5, A7, A9, A10) concurred that product development and management processes differ across companies, implying that product managers' responsibilities also vary. The implementa-

tion of AI solutions in the process depends on the product manager's responsibilities: "Before asking the question about AI applications in the product development and management process, it is important to inquire about the responsibilities of the product manager, because in every company, these responsibilities will differ. In one company, this might mean a product owner who manages a team of software developers, in another, a product marketing manager mainly responsible for the product's marketing campaign, and in yet another, a product manager accountable for the roadmap and profit and loss of the product [...]. In each of these cases, making such changes may not be part of the product manager's responsibilities" (Interview A4). Another respondent adds: "Sometimes, it is the

director or top management who dictates what the process should look like. Often, it also depends on the company size—in large corporations, there are dedicated individuals in charge of process improvement, while in start-ups, the product manager has more freedom but less time to enhance the process because the focus is on proving the product" (Interview A5). Respondents also agree that product managers currently possess limited knowledge of AI solutions, posing a challenge to the proposal to use these solutions for streamlining the product development and management process: "The product manager should take the time to understand what is possible in terms of AI solutions and how these solutions and the amount of data affect what they can achieve" (Interview A2). The majority of interviewees recognize that they had to change their thinking when dealing with products:

"There should be a greater focus on thinking that everything is data—every document, our conversation, audio, video—then it will be easier for product managers to grasp some of the difficulties and challenges of data, and for managers and senior management to accept it" (Interview A10). In some cases, the problem an AI model is meant to solve is too complex, or such a case has not existed before, causing the AI to query a human for an answer, e.g., an AI surveying product sentiment analysis is uncertain whether an opinion is positive or negative. This approach is commonly referred to as "Human In The Loop" (HITL). Respondents add: "Even if that human in the loop is a software developer, the product manager needs to have knowledge of the process and these solutions to participate" (Interview A9).

Process improvement as a product: Many respondents emphasize that before discussing AI applications or challenges, the matter of implementation must be addressed. "The introduction of any tool (AI or analytics) that could assist product managers in their daily work should simply be regarded as the creation of another product" (Interview A4). One respondent posits that it is easier to conceptualize such implementation when considering everything as a product: "If we wanted to launch, for example, a bicycle, then the bicycle is the core of the product, but the product encompasses everything around it, including the process of making the bicycle, marketing, selling, scaling, and so forth" (In-

terview A10). Respondents note that treating the process as a product in this manner also presents two additional challenges related to the timing and funding of such projects. If new tools were continuously proposed to enhance the process, there would be no time to manage and market the products that constitute the core of the business: "The best way to start is with a simple Minimum Viable Product (MVP) for such a tool, streamlining the process - build an MVP with a small amount of time and funding to demonstrate its value and show key stakeholders. However, an MVP is not production-ready, and that's where the risk lies - the time from MVP to actual implementation" (Interview A12).

4.2 Applications of AI in product development and management process

The discussions with respondents about AI applications and tools in the product development and management process revolved around two themes—current applications and tools, and those that could emerge to support the process. Respondents (A4, A8, A10) discussed the AI applications they currently observe during product development and management: "AI solutions during the product management process can be seen in microservices that suggest what to write, link up to-do shuffles, and recommend people" (Interview A4). Another adds: "It's all the tools related to Computer Vision, Natural Language Processing, Automatic Speech Recognition, Text-To-Speech, such as Google Docs, where AI solutions complete the sentence, that are able to help the product manager in the process" (Interview A8).

Some respondents (A3, A12) stated the need for a tool relieving them from not relevant tasks: "It would be highly beneficial if an AI solution introduced could relieve the product manager of all duties not related to creating a roadmap, being responsible for profit and loss, and focusing on new target groups" (Interview A3).

Other respondents (A4, A6, A11) indicate that it would be advantageous to have support during the new product development process phases: "It would be a great idea to have a tool that shows you what to concentrate on at any given time when creating a product, a tool that guides you through the process and assists

you in managing" (Interview A4). One respondent highlights that it depends on the product and describes what this looks like in the drug discovery niche: "AI solutions are useful at an early stage, i.e., in the product ideation and idea screening phase, where certain ideas need to be discarded, and with product design, where it can suggest new compounds" (Interview A9).

Another topic raised by the respondents (A6, A9) was decision making help for finalized product: "AI solutions could especially help with decision-making issues concerning the product, such as business model choices, prompting which elements of a prototype to test, or suggesting how to conduct A/B testing" (Interview A6).

4.3 Challenges of AI in product development and management process

When interviewed regarding the challenges of implementing AI solutions in the product development and management process, all respondents (A1–A12) agreed that the quantity and quality of available data are crucial. "If we would like to implement any AI solution that would assist in every phase of product implementation and subsequent management, the organization must possess vast amounts of data. Additionally, one must consider at what number of products, what number of sales, it makes sense to introduce such a solution and what decision it will help the product manager make" (Interview A2). Another adds: "Acquiring, cleaning, and preparing data so that it is ready for the AI model is the most difficult and time-consuming task. There is no generic program that by default collects data of different types, from different sources, and models it in such a way that the data is ready to be implemented in the AI model" (Interview A1). One respondent notes that an organization's maturity or readiness to use AI solutions, related to the collected data, is a significant factor: "Working as a consultant for AI implementations, there have been cases of companies where product managers wanted to streamline the product management process, but clients abandoned the idea because they were not yet at a level, in terms of data quantity and quality, to begin using AI solutions" (Interview A6). Respondents also observe that preparing a model itself is not difficult,

and it is often possible to use existing models—if a company has previously introduced models for sales prediction, for example, then it is possible to use that prediction in another process after minor modifications.

There is no methodology or framework that guides the use of AI in the product development and management process: "Organizations employ various methodologies, models, and techniques when developing new products, such as CRISP-DM, AgilePM, TDSP, and others, but there is no methodology or model that instructs on how best to approach AI products, whether developing a tool that supports a process or the AI solution is part of a product" (Interview A12). One interviewee suggests MLOps as a potential solution: "MLOps, as a set of practices, is not typically dedicated to AI-driven product development and management, but it could serve as the foundation for a methodology or framework" (Interview A1). According to another respondent, however, when creating such a framework based on another, one must ask: "Different companies have different approaches to product development; therefore, if we were to incorporate AI solutions that aid the product manager, the question arises: what would be the benefit of using AI in such a framework? We would need to have some measure that evaluates how a given AI solution helps, i.e., does it accelerate the process by X%, does it reduce the cost by Y%, etc." (Interview A11).

Another critical factor, which was mentioned earlier and is a significant challenge according to most respondents (A1, A3, A5, A6, A8, A9), is the attitude of people in the organization toward the use of AI solutions—product managers, engineers, and senior management. "When I was still working as an AI engineer and had meetings with the product manager regarding proposals to implement these solutions, even ones that could help the product manager on a day-to-day basis, what was important was the hard, cold numbers" (Interview A3). Another adds: "I often found myself talking to colleagues who worked as data scientists and, surprisingly, they preferred to work on projects where they didn't have to implement AI models. This was due to the fact that senior management often told them to improve the accuracy of the models indefinitely, which did not save as much money as the senior managers originally thought" (Interview A1).

Another frequently (A1, A4, A5, A7, A8, A11) mentioned challenge was security and privacy, especially if the product was implemented in sectors sensitive to these factors: "When working on a product that is implemented in, for example, banks or medical institutions, even if the AI solution does not support the product, but the process itself, security and privacy issues are at the forefront" (Interview A7). Another adds: "Let's say you want to introduce an AI solution that supports the development process of a new product—if you don't develop it yourself, there is a lot of risk in using external companies and tools by sharing data with them. In such cases, you want to know exactly who the company is that is introducing such a solution to you" (Interview A5).

Several respondents (A1, A2, A4, A5, A7, A8, A11) also emphasize the challenges of trust and explainability of AI solutions: "If we had a program that would take the data itself, input it into a model, and based on that do something or decide something, the issue of trust in that whole process arises—are we able to trust AI decisions without any oversight?" (Interview A1). Another respondent proposes a solution: "If we had a product manager using AI models to support the process, it would be better to explain the prediction, instead of just showing the prediction—instead of replacing the human, you can help them. So here we have a Human In The Loop solution, but with the addition of superhuman abilities" (Interview A4). As with security and privacy, trust factors and explainability are important in certain specific domains: "Depending on what the AI solution would help with in the product development process, it is important to remember that where we are dealing with financial, medical, or data center-related products, there is a much greater emphasis on explaining what is happening than in other sectors" (Interview A11).

One factor mentioned by respondents that is not often considered as a challenge in a project is computing power: "When implementing an AI solution, no matter the process, people often forget how important the computing power needed to produce the models is. This can even sometimes bring the whole project to a halt" (Interview A11). Another adds: "When implementing AI solutions, people usually do an estimate of the cost of implementing the models, but very often forget to estimate the cost of using the model. Later it turns out that the model is used hundreds of times in

a short period of time, and this consumes enormous amounts of computing power" (Interview A9).

4.4 Success factors of AI implementation in product development and management process

Respondents found it more challenging to discuss success factors when implementing AI solutions in the product development and management process compared to discussing challenges earlier. Some respondents (A1, A4, A7, A8, A9, A11) stress the need to have an appropriate metrics, e.g., financial. One respondent states: "We define product success financially—we have a financial plan, and if the product meets that plan, then it's a success. If we introduce a tool that improves the process of making that product or makes the product manager's job easier, then that should translate into a more successful product. The issue is just how to measure it" (Interview A4). Another interviewee also raises the issue of appropriate metrics: "There are two ways—one way, where we have two similar products with similar functionalities, we carry out the whole process of development of the first product and examine the time and resources it required, without using AI solutions, and on the second one, we carry out the same process but with AI tools and compare—but it is very time-consuming. The second way is where we have an AI tool, and we look at how the product manager performs with and without that tool. In the latter case, you would need to introduce some quantified measures" (Interview A7). One respondent believes that such a measure could be a satisfaction score, but one must exercise caution: "A good measure to determine the success of an AI tool being implemented in a process can be a satisfaction score, that is, we survey the satisfaction of the people who start using the tool. However, it is also a dangerous measure because it depends greatly on the people surveyed and the sample size, so the results can be distorted by various confounding factors" (Interview A8).

Other respondents (A1, A3, A5) presented the measure in the context of the feasibility and business impact of the implemented solution: "Working as a consultant for many companies on data and AI solutions, success was achieved by those companies that, in the process for the implemented solution, were able to answer well

in advance the question of how important and executable the solution is. To assess feasibility, one has to answer the questions of whether there is data available, whether this data is representative, whether it is technologically difficult or easy to engineer, whether there is knowledge available. To assess business impact, you often need a measure and, depending on the solution being introduced, you can conduct a market or competitor analysis here to determine what that measure might be" (Interview A5). Another significant point raised by respondents, referring to feasibility, is to consider whether AI is necessary in the process, even when data are available: "Once, we had a project where we aimed to improve the menu of one of our devices. To do this, we gathered data from different devices to see which menu items customers were using and which they weren't, then adjusted the menu so that all the most frequently used items were the most visible. This is data-driven product development or optimization, and we considered using AI, but found it was quicker to do it without it" (Interview A1). Another interviewee added: "We had one product where we knew from the beginning that we wanted to use AI solutions, specifically Computer Vision solutions, and this was not even subject to consideration, because the alternative was to hire numerous people who would have to write the algorithm for a given production and label the data, and the work on this project would end after a few months and all these people would have to be fired. Of course, we conducted a cost analysis in both cases anyway, but I want to emphasize that sometimes it is just evident that using AI solutions is far superior" (Interview A3).

Several respondents (A2, A3, A5, A7, A12) identify the quality of the team as one of the key measures of success: "The primary link between all the successful projects I was involved in as a product manager was the quality of the team. I am referring to individuals from various departments—sales, supply, approvals, etc." (Interview A2). Another interviewee emphasizes the importance of collaboration between departments: "Once, we aimed to improve data analytics related to our products in the product manager department to expedite certain functionalities. It turned out that to achieve this, we needed data from both sales and procurement to obtain information on the customers from whom we purchased products—often, these customers were the same ones who bought products from us.

It may seem astonishing, but these departments had never collaborated before, and it was only through the commonality of these tables that we could discern the full relationship with some companies. That kind of cross-departmental collaboration was crucial, and we, as product managers, have this helicopter view to initiate something like that" (Interview A12). Both above respondents (A2, A12) also indicated that having a single data dictionary in the organization was an important factor.

5 Discussion

The outcomes of this study enabled us to delve deeper into the applications, challenges, and success factors of AI-driven product development and management. Nevertheless, there were also two overarching themes that were emphasized by numerous respondents during the research, which were related to the studied research areas and might be thought-provoking for the future researchers. Pertaining to the first of the overarching themes, as raised by the respondents (A1, A2, A4, A5, A7, A9, A10), the responsibilities of a product manager frequently depend on the type of product or sector and the size of the company. In the case of smaller companies, it is much more likely that the product manager, in addition to being accountable for the product's profit and loss, will also have some marketing functions or be responsible for the software development team, as stated in interview A4. In the IT sector, there is often solely a product owner role, and the direction of the product is determined by senior management. It is also senior management that often decides on process-related improvements. However, new roles are emerging, such as Product Ops, whose responsibility is to enhance processes, alignment, and communication surrounding the product. Often, individuals in this role supply product managers with the appropriate data, enabling them to make informed business decisions and offload more operational and time-consuming tasks. This allows product managers to concentrate on product development and management. Such a role could also remove the need for product managers to have detailed knowledge of data and AI solutions, which respondents A2, A9, and A10 considered important. Examining the impact of this emerging role on the functioning of the product development and management process, in the context of the

growing commercial prevalence of AI solutions, could be a compelling research area for future researchers.

As for the second overarching theme, which involves introducing process improvement as a product, Product Ops role may also address that issue. As raised by respondents A4 and A10, every implementation, including process improvement, should be treated as a product. That also implies that the primary driver of this activity should be the product manager. However, this presents a challenging issue: if the product manager is responsible for introducing process improvements, it detracts from their time spent managing the products themselves. Therefore, a role like Product Ops can handle process improvement as part of their responsibilities without considering it a new product. This, however, does not solve the problem of funding such improvements, which respondent A12 points out as important. Such a new role, however, could focus on building a Minimum Viable Product (MVP) with a small budget to demonstrate to management with a request for funds. With a new role or not, pre-identifying key responsibilities of product managers and determining how to treat implementations of AI tools to support product development and management process can facilitate their implementation.

RQ1. How are companies currently using AI solutions in product development and management process and what are other desirable use cases?

In addressing RQ1, based on respondents' answers, AI solutions for product development and management can be generally categorized into four segments. The first segment encompasses everyday tools that support work processes (based on the interviews A4, A8, A10). Numerous AI solutions exist that can enhance the efficiency and effectiveness of product managers, such as tools that automatically complete sentences, suggest prioritized tasks, or identify areas for improvement. While these tools may be accessible to all organizational members, it is crucial to determine which are particularly beneficial for product managers and how they can be integrated into their workflows. It's worth noting that respondents had trouble pinpointing specific tools and tended to point to generally available tools (e.g., Google Docs, respondent A8) that have begun to use AI solutions to autocomplete sentences, for example.

The second segment comprises tools that alleviate tedious tasks for product managers, including automated data entry or report generation (based on the interviews A3, A12). Identifying which tasks are particularly time-consuming for product managers and how automation can be applied significantly improves their productivity and, consequently, product success. In this case, respondents had trouble pointing to even one existing tool, indicating more of a need for one.

Regarding the third segment, respondents (A4, A6, A11) expressed the need for an AI guide that can be utilized throughout the entire product lifecycle, with tools that assist in the product development and management process. This may include Natural Language Processing techniques for customer feedback analysis or Computer Vision solutions for product image examination. AI-driven chatbots or expert systems could guide product managers throughout the process, facilitating better decision making based on available data.

Lastly, the fourth segment involves tools that aid in decision making for finalized products (as raised by respondents A6, A9). Chatbots or expert systems could assist product managers in evaluating customer feedback and making informed decisions about product features or market strategy. This may involve analyzing A/B testing data to decide whether to launch a product in a specific market or discontinue a particular feature. In this case, as well, respondents had trouble identifying a specific tool.

In summary, while identifying AI solutions particularly useful to product managers and integrating them into their workflows are critical to successful product development and management, respondents struggled to identify specific solutions. Most often, they pointed to general-purpose solutions that are used by more than just product managers as support for basic day-to-day work. There was no indication of many of the solutions identified in the literature such as anomaly detection for product quality testing or, for example, sentiment analysis for assessing the positivity or negativity of product reviews. However, it is worth noting that respondents indicated a number of applications where they think solutions could help them, such as an AI-based guide for product development and management process or a tool to assist them in making business decisions for already finished products. Respondents acknowledged that implementing such solutions in the

company would mean that tasks would be completed faster and would increase efficiency.

RQ2. What are the challenges faced by companies looking to implement AI solutions in product development and management process, and how can the success of these implementations be determined?

In addressing RQ2, interviewee responses reveal that adopting AI-driven product development and management processes presents several challenges for organizations. One such challenge, as raised by all respondents (A1–A12), involves handling and processing large volumes of high-quality data to make better business decisions. Building accurate AI models that assist product managers in making informed decisions necessitates adequate data. Organizations must invest in technologies capable of efficiently processing and analyzing vast data volumes to extract meaningful insights. This requires significant computing power, as stated by respondents (A9, A11) and advanced algorithms, which can be expensive and time-consuming to implement and maintain. Security and privacy concerns are paramount in AI-driven product development and management as stated by respondents (A1, A4, A5, A7, A8, A11). Product data are often sensitive, and external companies using these data to build supporting tools for product managers can present potential security and privacy risks (as noticed by respondent A5). Organizations must implement appropriate security measures to protect product data and ensure its use for authorized purposes only. Trust and explainability of data shown to product managers pose another challenge as noted in interviews (A1, A2, A4, A5, A7, A8, A11). Product managers must understand AI models' decision-making processes to make informed decisions; otherwise, it is the issue of fully trusting AI, without any oversight, as raised in interview A4. Organizations should ensure AI models are transparent and explainable, building trust in the AI solutions, especially in financial, medical, and data center sectors, as noted by respondent A11. All the above data challenges are consistent with those found in the literature, which could mean that solving these challenges in the organization overall would help solve these challenges for the product development and management process as well.

Another challenge is people's approach to using AI solutions within the organization as raised by

respondents (A1, A3, A5, A6, A8, A9). While attitudes toward AI are generally positive, and people want to introduce it, unrealistic expectations about its impact on product sales and misunderstandings about the solutions and associated costs often exist, as raised, e.g., by respondent A1. One of the implications for organizations is that they should educate stakeholders on AI's capabilities and limitations, setting realistic expectations through training and awareness programs that clarify AI solutions' benefits and limitations. Challenges related to people's attitudes toward data and AI also overlap with those related in the literature, especially when it comes to not knowing enough, when it comes to what is possible (e.g., with infinite improvements in model accuracy as noted by respondent A1), or when it comes to looking primarily at profit (as noted in interviewee A3).

The lack of a clear methodology or model is a significant issue raised by respondents (A1, A11, A12). MLOps, proposed by respondent A1 as a basis for such a new model, is dedicated to implementing and maintaining machine learning models and includes a flywheel loop. Such flywheel loop could be added to the product development and management process, and the product manager (or the previously mentioned Product Ops role) would be responsible for following and maintaining such flywheel process. Another issue with the introduction of such a framework, as noted by the A11 interviewee, is that if AI solutions are introduced into the framework, there should also be clear deliverables on how such an introduction benefits the framework. This means that when introducing AI into a framework, the organization should know where it wants to get to, which may involve discussions on the organization's AI maturity and readiness. Respondents' indications are consistent with the literature in terms of the lack of a clear methodology for introducing AI solutions into the product development and management process.

Although all interviewees were engaged in product management, highly familiar with AI solutions, and mostly knowledgeable about research, pinpointing specific metrics relevant to AI-driven product development and management processes proved challenging for them; however, they stressed a need for it (as noted in interviews A1, A4, A7, A8, A9, A11). Respondents indicated that success evaluation metrics

could be, e.g., financial (interview A4) or time-based (interview A7), with companies determining these metrics through market or competitor analyses. Alternatively, satisfaction scores could be employed, as raised by interviewee A8, but these may be confounding factors as respondent mentioned that they do not necessarily reflect the actual success of the solution. Comparing these findings with the literature, in (McKinsey, 2021) cost reduction or revenue increases metrics were employed, so financial metrics and also satisfaction score, which were also discovered by the respondents. Other measures like risk mitigation or intangible measures like culture change or competitive advantage were also identified in the literature, which respondents did not identify as key. Some implication for organizations is that when trying to implement AI solutions in the product development and management process, some measure of success (financial, time-based, satisfaction-based, or other) should be implemented for implementation assessment.

Other respondents (A1, A3, A5) identified business impact and feasibility addressed in advance as crucial success factors. Business impact primarily refers to the imposed target, the aforementioned metric, and feasibility to considering the previously mentioned and other potential challenges, as raised by interviewee A5. Regarding feasibility, respondents indicated cases where using AI was obvious from the beginning of the project (interview A3) but also cases where it was considered but deemed not needed, as the solution without AI was quicker (interview A1). Quality and effective collaboration among teams are also essential success factors, as noted by several respondents (A2, A3, A5, A7, A12). As one respondent's (A12) example demonstrated, different departments or teams within an organization may work with the same data but employ different terms, definitions, or formats. This can result in inconsistencies and errors, hindering the effective use and sharing of data. Establishing a single data dictionary or framework, as noted by respondents (A2, A12), that provides a shared understanding of data definitions, formats, and relationships is important and can ensure consistency and accuracy. Regarding data dictionaries, data mesh architectures represent a relatively new approach to data management that is gaining popularity. In a data mesh architecture, data are

managed as a product, with individual teams responsible for the data products they create. Each data product is treated as a separate entity with its own domain-specific language and schema. This approach facilitates decentralized, scalable data management while maintaining a shared understanding of data across the organization. Possessing such understanding is a key component of an effective Knowledge Management (KM) model. Implementing KM strategies involving the aforementioned data mesh architecture can consequently result in more effective product decision making and improved business outcomes. While feasibility, business impact, team quality, and collaboration are important factors for success, many more can be found in the literature, both those typically affecting product success (such as innovative value or customer-centricity) and those related to AI solution implementation (such as design thinking in AI solution development engaging third-party companies for testing and validation of AI models).

6 Summary

This study identified several implications for product managers and organizations. First, most challenges mentioned by respondents apply to the entire organization; thus, if the organization can address these challenges, the solutions will also apply to AI tools introduced in the product development and management process. In this case, organizations can employ AI readiness or AI maturity frameworks to assess their current status and determine the steps necessary for effectively introducing specific AI solutions. Introducing a single data dictionary accessible to all departments within the organization can also be beneficial. Notably, innovative solutions like data mesh architectures warrant special attention. Another aspect involves changing the approach and educating those directly responsible for products about AI solution capabilities and associated costs. This training should also cover privacy, security, explainability, and trust related to data and AI solutions. Organizations should examine other companies that have successfully implemented such improvements, creating conditions that allow for accurate assessment of the business impact and feasibility of introduced AI solutions. The aforementioned AI maturity assessment can assist in this process since, at a certain maturity level with

the right processes in place, it becomes much easier to evaluate the introduction of a given project in advance and select the appropriate metric. Based on the responsibilities of product managers, organizations can contemplate ways to enhance their work. One potential solution involves hiring a Product Ops professional responsible for introducing AI solutions that can help product managers make better business decisions

about products or provide guidance during new product development. It is noteworthy that some overlap exists between the literature and the interviews, especially concerning the challenges related to data and people's approach to AI solutions, as well as success metrics. Table 3 summarizes these findings along with the potential future directions.

Table 3. Implications for product managers and organizations and possible future directions for researchers
(Source: Own study)

Implications/ future directions	Description
Implications for product managers and organizations	Pre-identifying key responsibilities of product managers and determining how to treat implementations of AI tools to support product development and management process can facilitate their implementation
	Implementing AI solutions that can support product managers in everyday tasks, relieve from tedious workflows, support in making product business decisions or guide through product development process can enhance their speed and work efficiency
	Addressing data challenges (quantity, quality, security, explainability, computing power to process the data) in the organization can benefit the product development and management process, as the challenges are similar
	Providing training for stakeholders involved in the product process about the capabilities and costs of AI solutions can help prevent unrealistic expectations
	Employing a proper methodology (AI readiness, AI maturity, or similar frameworks) can help companies assess the necessary steps for introducing AI solutions into the product development and management process
	Implementing measure of success (financial, time-based, satisfaction-based, or other) is important to properly assess implemented AI solution in product development and management process
	Accurately pre-assessing project challenges, evaluating the extent to which an AI solution will impact the process, quality team, and cross-departmental collaboration can increase the chances of success
	Implementing a general data dictionary in the organization that can be utilized by all departments (e.g., using data mesh architecture) can improve work efficiency across the organization
Future directions for researchers	Empirical study of organizations that use AI solutions in the product development and management process
	Investigation into the impact of the Product Ops role on the AI-driven product development and management process
	Research into methodologies or models for AI-driven product development and management processes
	Identification of the impact of organizational AI maturity or AI readiness on the product development and management process
	Data mesh architectures as part of an organizational knowledge management framework and their relationship to AI-driven product development and management processes

7 Conclusions, limitations, and future directions

The study presents exploration of the applications, challenges, and success factors in the product development and management process, where AI solutions are central. The chosen research approach was evaluated as appropriate, and answers to both research questions were found. Although respondents struggled to identify more current AI solutions, efficacy was rated as acceptable and efficiency as high, given the authors' time constraints. The identified factors are interconnected and interdependent. For example, an effective knowledge management framework can help mitigate the challenge of inadequate or low-quality data, while AI applications can be utilized to analyze and leverage the data more efficiently. The research also offers implications for organizations and future researchers. Many of the challenges and success factors discovered are relevant to the organization as a whole; therefore, addressing these challenges and adopting success factors at an organizational level will facilitate adaptation in the product development and management process. Assessing an organization's current AI readiness or AI maturity and providing AI application training can support the introduction of AI solutions, not only in the product process.

Regarding the study's limitations, the small qualitative sample and cross-sectional nature of the study may constrain its generalizability. However, the in-depth interviews conducted with individuals currently or previously involved in product management, deeply familiar with AI solutions, and in most cases with a scientific background, selected based on years of experience, provide a rich and detailed understanding of the current state of AI-driven product development and management. One suggested direction for future research is to create a survey with a larger sample to test the validity and generalizability of this study's findings. As for other potential directions for future research, most relate to the limited research in this field. One direction involves empirical studies of organizations using AI solutions in any product development phase or for making product-related business decisions. Researchers could focus on a specific sector, product type, or phase where these solutions are employed. Another interesting direction could be to study

the impact of the Product Ops role on the product development and management process, within the context of increasingly utilized AI solutions, and investigate the relationship and division of responsibilities between this role and that of the product manager.

Additional research could involve developing a general model for using AI solutions in the product development and management process, potentially based on the strategic flywheel. Here, the model itself and methodologies for designing such product strategic flywheels based on data and AI solutions pose intriguing challenges. Another direction could involve mapping organization-wide AI maturity or AI readiness onto the product development and management process or studying the impact of a certain degree of AI maturity on this process. An emerging topic of interest is data mesh architectures; examining them as a part of an organization's knowledge management framework and the impact this framework has on the product development and management process constitutes a potentially engaging research direction.

8 References

- [1] Aguwa, C., Olya, M.H. and Monplaisir, L., 2017. Modeling of fuzzy-based voice of customer for business decision analytics, *Knowledge-Based Systems*, 125, pp.136-145. <https://doi.org/10.1016/j.knosys.2017.03.019>.
- [2] Atsalakis, G., 2014. New technology product demand forecasting using a fuzzy inference system, *Operational Research*, 14(2), pp.225-236. <https://doi.org/10.1007/s12351-014-0160-y>.
- [3] Ballestar, M.T., Grau-Carles, P. and Sainz, J., 2019. Predicting customer quality in e-commerce social networks: a machine learning approach, *Review of Managerial Science*, 13(3), pp. 589-603. <https://doi.org/10.1007/s11846-018-0316-x>.
- [4] Bosch, J., 2019. From efficiency to effectiveness: Delivering business value through software, *Lecture Notes in Business Information Processing*, 370 LNBIP, pp.3-10. https://doi.org/10.1007/978-3-030-33742-1_1.
- [5] Bosch, J., Olsson, H.H. and Crnkovic, I., 2018. It takes three to tango: Requirement, outcome/data, and AI driven development, in. *CEUR Workshop Proceedings*, pp. 177-192.
- [6] Burgess, A., 2018. *The Executive Guide to Artificial Intelligence*. Cham: Springer International Publishing. <https://doi.org/10.1007/978-3-319-63820-1>.

- [7] Byrd, M. and Darrow, R., 2021. A note on the advantage of context in Thompson sampling, *Journal of Revenue and Pricing Management*, 20(3), pp.316-321. <https://doi.org/10.1057/s41272-021-00314-1>.
- [8] Chen, J.-S., Le, T.-T.-Y. and Florence, D., 2021. Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing, *International Journal of Retail and Distribution Management*, 49(11), pp.1512-1531. <https://doi.org/10.1108/IJRDM-08-2020-0312>.
- [9] Chen, T. and Wang, Y.-C., 2018. A fuzzy collaborative intelligence approach for estimating future yield with DRAM as an example, *Operational Research*, 18(3), pp.671-688. <https://doi.org/10.1007/s12351-017-0312-y>.
- [10] Cricelli, L., Grimaldi, M. and Vermicelli, S., 2022. Crowdsourcing and open innovation: a systematic literature review, an integrated framework and a research agenda, *Review of Managerial Science*, 16(5), pp.1269-1310. <https://doi.org/10.1007/s11846-021-00482-9>.
- [11] Cubric, M., 2020. Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study, *Technology in Society*, 62. <https://doi.org/10.1016/j.techsoc.2020.101257>.
- [12] Desouza, K.C., Dawson, G.S. and Chenok, D., 2020. Designing, developing, and deploying artificial intelligence systems: Lessons from and for the public sector, *Business Horizons*, 63(2), pp.205-213. <https://doi.org/10.1016/j.bushor.2019.11.004>.
- [13] Duan, Y., Edwards, J.S. and Dwivedi, Y.K., 2019. Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda, *International Journal of Information Management*, 48, pp.63-71. <https://doi.org/10.1016/j.ijinfomgt.2019.01.021>.
- [14] Eren, B.A., 2021. Determinants of customer satisfaction in chatbot use: evidence from a banking application in Turkey, *International Journal of Bank Marketing*, 39(2), pp.294-311. <https://doi.org/10.1108/IJBM-02-2020-0056>.
- [15] Figalíst, I., Elsner, C., Bosch, J. and Olsson, H.H., 2020. Breaking the Vicious Circle: Why AI for software analytics and business intelligence does not take off in practice, in: *Proceedings - 46th Euromicro Conference on Software Engineering and Advanced Applications*, SEAA 2020, pp.5-12. <https://doi.org/10.1109/SEAA51224.2020.00013>.
- [16] Flick, U., 2023. *An Introduction to Qualitative Research*, SAGE Publications Ltd.
- [17] Garg, P., Patil, A., Soni, G., Keprate, A. and Arora, S., 2021. Machine learning-based abnormality detection approach for vacuum pump assembly line, *Reliability: Theory and Applications*, 16, pp.176-187. <https://doi.org/10.24412/1932-2321-2021-264-176-187>.
- [18] Giannakis, M., Dubey, R., Yan, S., Spanaki, K. and Papadopoulos, T., 2022. Social media and sensemaking patterns in new product development: demystifying the customer sentiment, *Annals of Operations Research*, 308(1–2), pp.145-175. <https://doi.org/10.1007/s10479-020-03775-6>.
- [19] Gurkan, H. and de Véricourt, F., 2022. Contracting, Pricing, and Data Collection Under the AI Flywheel Effect, *Management Science*, 68(12), pp.8791-8808. <https://doi.org/10.1287/mnsc.2022.4333>.
- [20] Huang, T., Bergman, D. and Gopal, R., 2019. Predictive and Prescriptive Analytics for Location Selection of Add-on Retail Products, *Production and Operations Management*, 28(7), pp.1858-1877. <https://doi.org/10.1111/poms.13018>.
- [21] Hughes, G.D. and Chafin, D.C., 1996. Turning New Product Development into a Continuous Learning Process, *Journal of Product Innovation Management*, 13(2), pp.89-104. <https://doi.org/10.1111/1540-5885.1320089>.
- [22] Jain, T., Meenu and Sardana, H.K., 2020. Quality edge extraction of mechanical CAD parts for intelligent manufacturing, *International Journal of Process Management and Benchmarking*, 10(1), pp.22-47. <https://doi.org/10.1504/IJPMB.2020.104230>.
- [23] Jin, B.E. and Shin, D.C., 2020. Changing the game to compete: Innovations in the fashion retail industry from the disruptive business model, *Business Horizons*, 63(3), pp.301-311. <https://doi.org/10.1016/j.bushor.2020.01.004>.
- [24] Johnson, P.C., Laurell, C., Ots, M. and Sandström, C., 2022. Digital innovation and the effects of artificial intelligence on firms' research and development – Automation or augmentation, exploration or exploitation?, *Technological Forecasting and Social Change*, 179, p.121636. <https://doi.org/10.1016/j.techfore.2022.121636>.
- [25] Koulouriotis, D.E. and Mantas, G., 2012. Health products sales forecasting using computational intelligence and adaptive neuro fuzzy inference systems, *Operational Research*, 12(1), pp.29-43. <https://doi.org/10.1007/s12351-010-0094-y>.
- [26] Langone, R., Cuzzocrea, A. and Skantzou, N., 2020. Interpretable Anomaly Prediction: Predicting anomalous behavior in industry 4.0 settings via regularized logistic regression tools, *Data and Knowledge Engineering*, 130. <https://doi.org/10.1016/j.datak.2020.101850>.
- [27] Lee, I. and Shin, Y.J., 2020. Machine learning for enterprises: Applications, algorithm selection, and

- challenges, *Business Horizons*, 63(2), pp.157-170. <https://doi.org/10.1016/j.bushor.2019.10.005>.
- [28] Liao, Y., Ragai, I., Huang, Z. and Kerner, S., 2021. Manufacturing process monitoring using time-frequency representation and transfer learning of deep neural networks, *Journal of Manufacturing Processes*, 68, pp.231-248. <https://doi.org/10.1016/j.jmapro.2021.05.046>.
- [29] Liebe, U. and Meyerhoff, J., 2021. Mapping potentials and challenges of choice modelling for social science research, *Journal of Choice Modelling*, 38. <https://doi.org/10.1016/j.jocm.2021.100270>.
- [30] Luo, Z., Huang, S. and Zhu, K.Q., 2019. Knowledge empowered prominent aspect extraction from product reviews, *Information Processing and Management*, 56(3), pp.408-423. <https://doi.org/10.1016/j.ipm.2018.11.006>.
- [31] Luoma, J., Ruutu, S., King, A.W. and Tikkanen, H., 2017. Time delays, competitive interdependence, and firm performance, *Strategic Management Journal*, 38(3), pp.506-525. <https://doi.org/10.1002/smj.2512>.
- [32] Magistretti, S., Dell'Era, C. and Messeni Petruzzelli, A., 2019. How intelligent is Watson? Enabling digital transformation through artificial intelligence, *Business Horizons*, 62(6), pp.819-829. <https://doi.org/10.1016/j.bushor.2019.08.004>.
- [33] McKinsey, 2021. *Global survey: The state of AI in 2021* McKinsey. [online] Available at: <<https://www.mckinsey.com/capabilities/quantumblack/our-insights/global-survey-the-state-of-ai-in-2021>> [Accessed: 29 January 2023].
- [34] Mishra, A.N. and Pani, A.K., 2020. Business value appropriation roadmap for artificial intelligence, *VINE Journal of Information and Knowledge Management Systems*, 51(3), pp.353-368. <https://doi.org/10.1108/VJIKMS-07-2019-0107>.
- [35] Paschen, U., Pitt, C. and Kietzmann, J., 2020. Artificial intelligence: Building blocks and an innovation typology, *Business Horizons*, 63(2), pp.147-155. <https://doi.org/10.1016/j.bushor.2019.10.004>.
- [36] Patil, D.J. and Mason, H., 2015. *Data Driven*. O'Reilly Media, Inc.
- [37] Prem, E., 2019. Artificial intelligence for innovation in Austria, *Technology Innovation Management Review*, 9(12), pp.5-15. <https://doi.org/10.22215/timreview/1287>.
- [38] Puntoni, S., Reczek, R.W., Giesler, M. and Botti, S., 2021. Consumers and Artificial Intelligence: An Experiential Perspective, *Journal of Marketing*, 85(1), pp.131-151. <https://doi.org/10.1177/002242920953847>.
- [39] Pustokhina, I.V., Pustokhin, D.A., Aswathy, R.H., Jayasankar, T., Jeyalakshmi, C., Díaz, V.G. and Shankar, K., 2021. Dynamic customer churn prediction strategy for business intelligence using text analytics with evolutionary optimization algorithms, *Information Processing and Management*, 58(6). <https://doi.org/10.1016/j.ipm.2021.102706>.
- [40] Santana, M. and Díaz-Fernández, M., 2022. Competencies for the artificial intelligence age: visualisation of the state of the art and future perspectives, *Review of Managerial Science* [Preprint]. <https://doi.org/10.1007/s11846-022-00613-w>.
- [41] Soltani-Fesaghandis, G. and Pooya, A., 2018. Design of an artificial intelligence system for predicting success of new product development and selecting proper market-product strategy in the food industry, *International Food and Agribusiness Management Review*, 21(7), pp.847-864. <https://doi.org/10.22434/IFAMR2017.0033>.
- [42] Symeonidis, S., Peikos, G. and Arampatzis, A., 2022. Unsupervised consumer intention and sentiment mining from microblogging data as a business intelligence tool, *Operational Research*, 22(5), pp.6007-6036. <https://doi.org/10.1007/s12351-022-00714-0>.
- [43] Tubadji, A., Huang, H. and Webber, D.J., 2021. Cultural proximity bias in AI-acceptability: The importance of being human, *Technological Forecasting and Social Change*, 173, p.121100. <https://doi.org/10.1016/j.techfore.2021.121100>.
- [44] Viswanandhne, S., Kumar, A.S., Elwin, G.R., Priya, R., Praveen, V. and Priyanka, S., 2019. Improved decision making and enhanced recommendation systems in applications made possible through prescriptive analytics, *International Journal of Scientific and Technology Research*, 8(10), pp.2231-2233.
- [45] Zhang, M., Fan, B., Zhang, N., Wang, W. and Fan, W., 2021. Mining product innovation ideas from online reviews, *Information Processing and Management*, 58(1). <https://doi.org/10.1016/j.ipm.2020.102389>.
- [46] Zhao, D., Xue, D., Wang, X. and Du, F., 2022. Adaptive vision inspection for multi-type electronic products based on prior knowledge, *Journal of Industrial Information Integration* [Preprint]. <https://doi.org/10.1016/j.jii.2021.100283>.
- [47] Zitar, A., 2023. Can artificial intelligence's limitations drive innovative work behaviour?, *Review of Managerial Science* [Preprint]. <https://doi.org/10.1007/s11846-023-00621-4>.