A Cross-Disciplinary Knowledge Management Framework for Generative Artificial Intelligence in Product Management: A Case Study From the Manufacturing Sector

Aron Witkowski and Andrzej Wodecki
Warsaw University of Technology, Warsaw, Poland

aron.witkowski.dokt@pw.edu.pl
andrzej.wodecki@pw.edu.pl

Abstract: This paper presents a cross-disciplinary knowledge management framework designed to enhance the integration of Generative Artificial Intelligence (GenAI) in product management within the manufacturing sector. The framework focuses on designing, monitoring, and optimizing the business value of GenAI solutions by leveraging best practices from both knowledge management and artificial intelligence engineering disciplines. The study highlights the use of LLMOps methodology for continuous monitoring and multi-agent approach for continuous improvement. The research employs a qualitative case study methodology, focusing on a leading large international manufacturing firm that has implemented GenAI solutions in its product management. The study involves interviews with stakeholders and document collection and analysis. This case study contributes to the literature by providing a structured approach to incorporating GenAI into product management in the manufacturing sector, facilitating cross-disciplinary knowledge sharing. The study advances the understanding of using cross-disciplinary knowledge management framework for advanced AI applications in business projects and encourages further research. The framework serves also as a guide for manufacturing firms aiming to implement advanced AI providing actionable insights for designing, monitoring, and optimizing the business value of GenAI solutions. It underscores the potential of academic researchers as catalysts in such projects and proposes a method for continuous knowledge transfer and improvement through a knowledge flywheel.

Keywords: Knowledge Management, Generative Artificial Intelligence, New Product Development, Cross-Disciplinary Collaboration, Product management, Manufacturing

1. Introduction

Generative Artificial Intelligence (GenAI) plays a noticeable role in different industries, as evidenced by its potential in automating tasks, delivering novel goods, services or business models and generating valuable new content (Daugherty et al., 2023; Kanbach et al., 2024; Przegalinska and Jemielniak, 2023; Reznikov, 2024) The integration of GenAI in product management can potentially enhance innovation and streamline processes. Generative AI, particularly through large language models (LLMs) like the generative pretrained transformer (GPT), augments product processes including ideation, digital design and prototyping or product marketing (Bouschery et al., 2023; Bulut and Mahmoud, 2023; Choi et al., 2023).

The manufacturing sector, facing intense competition and the need for differentiation, can benefit from the integration of GenAI solutions in the product management process. Not only processes but also products undergo changes - one of the critical issues though in the manufacturing industry is the increasing difficulty in achieving hardware-based innovations (Smith, 2013). As a result, companies are shifting their focus towards additional services and connected products to maintain a competitive edge (Parida et al., 2014; Porter and Heppelmann, 2015). GenAI models can also be helpful here, but they come with their own challenges - hallucinations, data drift, ethical issues, and others, making it difficult to determine the business value of a GenAI (Bandi et al., 2023; Kalam et al., 2024; Samuelson, 2023).

This shift necessitates the development of new competencies among different stakeholders involved in product management to design and monitor the real business value generated by GenAI-driven solutions. Product managers must acquire certain new skills to effectively oversee the implementation, optimization and business evaluation of advanced AI-driven solutions. Data scientists, aiming to maintain the quality of GenAI models, must keep track of the latest solutions. However, the heavy workload and project overload often faced by product managers, IT engineers or data scientists pose challenges to acquiring these new competencies.

Therefore, the successful implementation of GenAI solutions requires a robust framework that supports the design, monitoring, and optimization of these technologies' business value. This framework can leverage best practices from knowledge management to ensure that the integration of GenAI not only enhances product management but also contributes to continuous learning and improvement within organizations. In the upcoming sections, we will explore a variety of insights and observations, primarily based on a case study of a leading manufacturing company, highlighting different facets of the relationship between knowledge management, generative AI and product management. These insights will shed light on the challenges and opportunities encountered when integrating advanced AI solutions into product management processes and the importance of multidisciplinary teams in overcoming these challenges. We will examine the importance of communication and collaboration among various stakeholders, the necessity of aligning business goals with technology objectives, and the influence of emerging technologies on the development of new products. Finally, we will emphasize the lessons learned from these observations and their implications for both practitioners and researchers in the realms of knowledge management, generative AI and product management.

2. Business Value From Generative Artificial Intelligence for Product Management

In this section we focus on the Generative Artificial Intelligence (GenAI) solutions impact on the product success. There are numerous activities in which GenAI can support the product management process. Sentiment analysis and opinion mining are useful for generating new product ideas and designing products. GenAI solutions such as BERT, GPT, LSTM, and N-gram language models often form parts of larger sentiment analysis solutions (Li et al., 2023). These are used, for example, to identify important elements in user-generated content (Wang and Liu, 2023), improve opinion mining through text and emoji fusion (Sai et al., 2023), or detect fake news about products (Peng and Xintong, 2022). Tools like ChatGPT can also generate product ideas and often do so more effectively than humans (Bouschery et al., 2023). GenAI can also be applied to text summarization in various contexts, enhancing recommendation systems by integrating summaries from online reviews (Benham et al., 2022). In product design and development across different industries, GenAI solutions facilitate tasks such as fashion design (Choi et al., 2023), cosmetic color scheme development (Zhang et al., 2023) and bionic-inspired biomedical engineering (Deng et al., 2023). They also aid in IT system design (Van Bossuyt et al., 2023), user interface design (Gupta et al., 2024), and game development (Colado et al., 2023). GenAI also supports product quality control and defect detection, generating new artificial data and reducing testing time, cost and TTM (Time-To-Market) (Morizet et al., 2023). Generative AI solutions are also effective in product marketing and the optimization of products processes. In marketing, GenAI is used for creating targeted advertisements and generating keywords (Bulut and Mahmoud, 2023), as well as in the automatic generation of promotional videos, which significantly streamline the creation of marketing content (Ooi et al., 2023). Additionally, they support customer service by providing potential recommendations for products and services (Sun et al., 2023). GenAI solutions are also effective at the intersection of product management and knowledge management, enhancing the functionality of product databases (Abadi et al., 2023; Niemir and Mrugalska, 2023). These benefits of GenAI integration can only be fully realized if the implementation of GenAI is managed effectively, using appropriate methodologies and evaluation methods.

2.1 Product Success Evaluation Methods

When evaluating product success, two key aspects need consideration: the factors contributing to success and the measurement of success. General product success factors identified in the literature include innovative value, strategic approach, high-quality product development processes, market research, customer focus, and maintaining skilled employees with the necessary resources and infrastructure (Soltani-Fesaghandis and Pooya, 2018). McKinsey (2021) identified several categories that distinguish high-performing AI organizations from others, including clear AI solution management models, team skill development programs, and practical training for non-technical staff. Additionally, factors such as design thinking in developing AI solutions, harmonized data processes, and regular updates and understanding of AI models play a distinct role in the successful implementation of AI in product management.

When it comes to the measurement of success, evaluating the business value of GenAI solutions is crucial for understanding their impact on product success. Three primary evaluation methods can be used: statistical methods, business methods, and experimental methods. Each of these methods has its impact in assessing GenAI models:

Statistical Methods: Common evaluation metrics for generative models include Fréchet Inception Distance (FID) and Inception Score (IS), although these can be prone to biases and may not always provide accurate comparisons between different models (Bandi et al., 2023; Chong and Forsyth, 2020).

Business Methods: These methods focus on the actual impact of GenAI solutions on business processes and product success. Metrics include Key Performance Indicators (KPIs) such as product revenue, process efficiency or product quality, which are more aligned with business objectives.

Experimental Methods: Used to assess the real business value post-deployment through A/B testing or surveys/qualitative interviews and other experimental designs that compare the performance of GenAI-driven solutions with existing methods.

Overemphasis on one area can lead to an unbalanced focus, causing some issues. A predominance of statistical methods may result in evaluations that do not align with business needs or are not easily understood by business stakeholders. A predominance of business method may lead to an overload of business metrics, complicating GenAI model training, evaluation, validation, and experimentation. A predominance of experimental approaches can create challenges in formulating business cases based on historical data and in the training process.

2.2 Lack of Appropriate Methodology

As commercial GenAI solutions are still in their relatively early stages, there is no comprehensive set of guidelines for managing GenAI-based products tailored to specific products or sectors. Bosch, Olsson, and Crnkovic (2018) highlight that AI development is still in its infancy in many of the organizations they have studied, and they foresee a considerable amount of work needed to define systematic and repeatable methods for creating, developing, and maintaining systems using AI solutions. This implies that when introducing GenAI into the process, the organization should have a clear understanding of its goals, which may require a discussion about the organization's maturity in that area.

To address these challenges, continuous monitoring and adaptation of GenAI models are necessary. One potential solution is the implementation and maintenance of the models based on a feedback loop strategy, which helps product managers create less prescriptive product roadmaps and make more data-driven and AI-based decisions (Gurkan and de Véricourt, 2022). Techniques such as LLMOps (Large Language Models Operations) for continuous monitoring and multi-agent approach for ongoing improvement can be helpful in that area.

LLMOps involve the methodologies, strategies, and tools employed for the effective management and maintenance of large language models in production settings. LLMOps is essential for managing the complex lifecycle of LLM development, which includes data ingestion, prompt engineering, model fine-tuning, deployment, and monitoring. It ensures collaboration across teams and maintains operational rigor. LLMOps differ from traditional Machine Learning Operations (MLOps) by addressing the unique needs of managing LLMs. Key considerations include the substantial computational resources required for training and fine-tuning LLMs, often necessitating specialized hardware like GPUs. LLMs typically use transfer learning from foundation models, and human feedback, including reinforcement learning, is crucial for their performance. The development of LLM applications also frequently emphasizes constructing pipelines, created using tools like LangChain or LlamaIndex that integrate multiple calls with external systems, instead of developing new LLMs from scratch (Kulkarni et al., 2023; Shi et al., 2024).

An AI multi-agent system is a decentralized network consisting of multiple intelligent agents capable of sensing, learning, and acting independently to accomplish objectives. Agents utilize their interactions with nearby agents or their environment to learn new contexts and actions. They then apply this acquired knowledge to make decisions and take actions within the environment to accomplish their assigned tasks. Driven by artificial intelligence, these systems exhibit essential features such as flexibility that enables it to effectively address problems across different industries (Dorri et al., 2018; Shamshirband et al., 2013).

3. Knowledge Management Framework for Designing, Monitoring and Optimizing the Business Value of Generative Artificial Intelligence Solutions in Product Management

This chapter builds upon established principles of knowledge management and product management, integrating insights from previous research and best practices to create a comprehensive framework tailored for GenAI in product management.

3.1 Competency Framework

A successful implementation of GenAI solutions in product management necessitates a multidisciplinary team with a diverse set of competencies. Drawing from the competency profiles discussed in (Wodecki, 2023), the framework identifies four key competency groups: business (senior management and/or product managers in that case), data science, experiment design, and information technology. Each role within the project - ranging from business representatives to data scientists and IT engineers - requires a unique blend of these competencies:

T-shaped Competencies: Business representatives should have deep business knowledge complemented by skills in data science and IT, allowing them to effectively plan business cases, monitor project execution, and manage business value comprehensively.

Pi-shaped Competencies: Data scientists need in-depth skills in data science and a robust understanding of business and software engineering. Experiment design skills are also crucial, forming a second vertical bar in their competency profile.

M-shaped Competencies: Either product or project managers must possess a wide array of horizontal competencies, including product management, project management, change management, and business acumen, along with vertical competencies in data science, IT, and experiment design.

Individuals involved in the project, including business owners, data scientists, IT engineers, and product/project managers, should possess a balanced mix of T-shaped, Pi-shaped, or M-shaped competencies. The success of the project depends on the effective flow of knowledge from these areas, both within the current project scope and by utilizing experiences from similar past endeavors. Imbalances in these skill sets can lead to errors in evaluating the business value of GenAI solution. Our observations reveal that while data science and IT competencies are gradually becoming widespread in mature organizations, expertise in experimental design and implementation remains a challenge for many. Therefore, as part of the knowledge management framework, it is beneficial to consider including external individuals in the team, such as representatives from academia. These individuals can introduce new ideas, methods, and techniques, and provide fresh perspectives on the problem, ultimately enhancing the quality of the solution. Moreover, mature experimental design and implementation methods from the scientific community can help address competency gaps in this area.

3.2 Knowledge Management Processes

The integration of Generative Artificial Intelligence (GenAI) solutions into product management projects involves different aspects of knowledge management, from knowledge creation to sharing and application. GenAI integration projects have distinct characteristics and potential as rich sources of knowledge. Methods for capturing, organizing, storing, and sharing knowledge are explored to provide insights into effective strategies for managing knowledge in this context. The integration of GenAI solutions in product management projects generates valuable knowledge due to their unique nature, addressing diverse business challenges with varied methods and technologies. Knowledge is created throughout the project, often during meetings, milestone summaries, documentation, and experimental results interpretation. Different methods such as automatic tagging, topic modeling or semantic embeddings are employed for knowledge organization. For storing knowledge, advanced methods like prompt retrieval, document embeddings, or pretrained generative model weights are suggested. Efficient knowledge sharing and application depend on accessible interfaces, and the use of conversational interfaces based on generative technologies can address the issue of scattered documents across various locations.

All the aforementioned processes can be evaluated in terms of their maturity, i.e., higher maturity of these processes can facilitate easier integration of GenAI solutions in product management. Different frameworks can be used to assess an organization's maturity in this area. For example, the CLIMB framework (Rossi and Terzi, 2017) is used to evaluate best practices in product management. The model was designed using a combination of theory-driven and practitioner-based approaches. The CLIMB model comprises five maturity levels (Chaos, Low, Intermediate, Mature, Best Practice), selected for their similarity to existing maturity models and assessment tools. The framework categorises 107 product management best practices, across eight areas: activities and flow, decision making, training, roles and collaboration, knowledge management processes, knowledge management techniques, methods, computerisation and software, respectively grouped into four categories: process, people, knowledge management and tools. A questionnaire with a five-point Likert scale can be used to evaluate each of the practices.

3.3 Knowledge Flywheel Framework for GenAI in Product Management

Considering previous discussions on the processes and maturity of knowledge management within organizations, different types of competencies, the involvement of academic representatives in projects requiring experimental design skills, the lack of appropriate methodology, and the use of loop strategies, and drawing upon (Wodecki, 2023), we propose a knowledge management flywheel framework for GenAI solutions integration in product management utilizing the Business-Engineer-Academy triangle. A strategic flywheel effect is achieved through continuous iterations of knowledge flow among business representatives, engineers, and academic researchers. This iterative process enhances understanding and improves efficiency and maturity of the processes resulting in greater product success.

To determine the accuracy of this framework, it was assessed using semi-structured interviews and open-ended discussions with a mixed group of 12 practitioners. This validation step is based on the evaluation phase of Design Science Research (Peffers et al., 2006) and is a crucial step in the development of many models in the literature. The panel included a balanced mix of individual contributors and those with managerial responsibilities, all of whom had experience working in an AI team (as either product manager or an engineer) within the organization. Their insights on the usefulness, reliability, and effectiveness of the framework were gathered, as they are considered the primary users of this framework.

The triangle works as follows: the business owners identify key performance indicators (KPIs) expected to improve with the implementation of a GenAI solution, the engineering team (comprising data science and IT professionals) executes the technical implementation and the scientists propose and perform experiments, analyze results, validate hypotheses, and present key findings to business stakeholders. With the new insights, the business suggests further experiment iterations and refines success metrics.

A well-structured Knowledge Management (KM) flywheel ensures continuous enhancement of managing the value of GenAI solutions integration in product management, moving beyond just model monitoring and diagnostics. This is achieved through systematic processes for generating, capturing, organizing, storing, and sharing knowledge throughout the project lifecycle (improving knowledge management maturity) and the application of methods such as multi-agent approach to optimize business experiments.

Thus, an exemplary KM flywheel (shown in Figure 1) might operate as follows:

1. New experiments lead to new insights…
2. …facilitating a better understanding of the business and thus…
3. …enhancing:
    a. business efficiency,
    b. internal KM processes and its maturity,
    c. product management process resulting in higher product value and…
4. …motivating the organization to undertake further experiments.

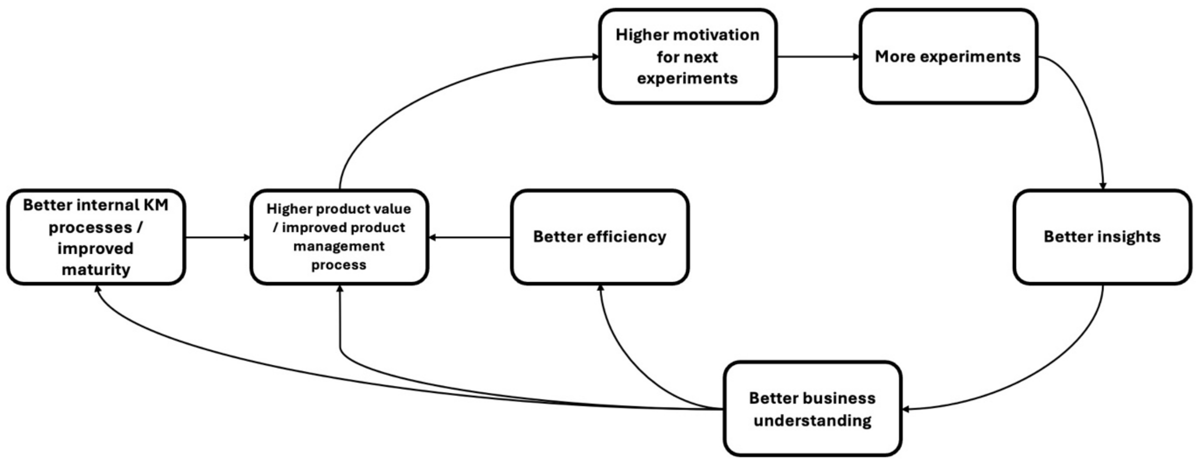

Figure 1: An exemplary Knowledge Management strategic flywheel for GenAI integration in product management process. Source: own elaboration.

4. Case Study

This case study examines the implementation of the proposed knowledge management framework for Generative Artificial Intelligence (GenAI) in product management at XYZ, a leading company in the manufacturing sector, present in all global markets, with locations in more than 30 countries. The study explores the processes and strategies employed by XYZ to integrate GenAI solutions into their product management practices, highlighting the challenges faced and the adopted path.

XYZ is a globally recognized leader in the production of industrial machinery. The company has a long history of innovation and has consistently invested in advanced technologies to maintain its competitive edge. Recognizing the potential of GenAI, XYZ embarked on a strategic initiative to integrate GenAI solutions into its product management processes.

Product management encompasses both operational tasks (e.g., delivering a product to market) and strategic tasks (e.g., predicting sales for a given product portfolio, creating a product roadmap for the coming years). For certain strategic tasks, such as predicting sales for a product portfolio, "simple" machine learning predictive models can assist by integrating data from different sources (historical sales data, product availability in stock, upcoming major projects).

Interviews conducted within company XYZ identified one primary issue related to strategic tasks, which became the focus of this study. The issue pertains to developing a unified roadmap for multiple diverse product portfolios that utilize the same resources (both engineering and marketing). It was found that many New Product Development (NPD) projects experience significant delays, which continue to escalate. Insufficient engineering resources led, for example, to engineers switching from project to project without having adequate time to fully understand the requirements, resulting in the creation of products with technical issues (failing to pass required tests).

The consideration of hiring additional personnel to increase available human resources proved challenging for several reasons. Firstly, this specific manufacturing sector is quite niche, and finding and onboarding new employees, particularly in engineering roles, is estimated to take 1-2 years, and in extreme cases, up to 3 years before the employee starts making a noticeable impact. Secondly, the high market dynamics result in scenarios where hiring may be feasible in one year, but cost-cutting measures may be necessary the following year, jeopardizing employee retention. Therefore, alternative methods were explored to enhance the efficiency of existing teams in developing roadmaps for various product portfolios, without increasing headcount.

To this end, a collaboration with academia was initiated, not only to alleviate the burden on the current team, already handling multiple projects, but also to approach the problem from a different perspective. This project was spearheaded by the product director (acting as a project manager, overseeing several product managers) and included the academic representative, selected product managers (responsible for different product portfolios), dedicated data scientists, and IT engineers. Each company representative (product managers, engineers) was able to dedicate a few hours weekly to work with the academic representative.

The first challenge encountered was data access. The academic representative had to define the scope of data usage and sign a non-disclosure agreement (NDA). Another challenge was the company's approach to GenAI; the company sought to implement GenAI responsibly. Currently, access to tools such as ChatGPT is blocked on all employee computers to prevent the use of company data in interactions with the chat, as the data processing methods are unknown.

At the design stage, it was decided to experimentally assess the business value of the GenAI solution. Consequently, it was necessary to develop an experiment plan and prepare the appropriate IT architecture. Considering the aforementioned restrictions, the academic representative proposed that, instead of building separate infrastructure within the company, the GenAI model would be hosted on a separate server prepared by the representative, over which the company's IT engineers would have supervision. This proposal was accepted.

The planning of the experiment largely focused on selecting the documents and determining which information the GenAI model should utilize to address the problem. This was done through the analysis of documents available in the organization (various product-related files, previous product roadmaps, and other information) as well as through interviews with stakeholders. Efforts were made to gather as much information as possible, ranging from the team structure to details about the construction of current products from each portfolio.

The selection of an appropriate evaluation method and metric, which would help assess the business value of the model, was also crucial. Choosing between statistical, business, and experimental evaluation methods, the scientist proposed using the experimental evaluation method due to the experimental nature of the implementation. The metric suggested by the scientist was a survey with a net promoter score for the solution proposed by the GenAI model, along with space for additional comments. Specifically, all project participants (product managers, engineers) would rate the responses of the GenAI model on a scale of zero to ten. The experiment would be repeated, adding new information or incorporating new requirements, until the average score of all ratings exceeds eight. This proposal was accepted.

Collecting information and establishing the metric served as a test of the effectiveness of the internal knowledge management processes. Upon completing the planning stage, the company was assessed using the CLIMB framework by the scientist, who filled out a questionnaire based on interviews with product managers. The company achieved the third maturity level (out of five) overall, as well as the third level in the knowledge management category. According to the scientist, based on the responses and the achieved score (level three corresponds to the Intermediate level), the organization could consider implementing GenAI solutions in the product management process without any noticeable process changes. However, it also helped the organization identify areas needing improvement, particularly in managing knowledge when introducing changes to the process rather than developing a new product. This was evident from the beginning when integrating data from some sources proved challenging.

During the implementation and evaluation phase of the model, the scientist proposed using the LLMOps methodology for effective model management and maintenance, as well as a multi-agent approach to increase efficiency and optimize computational resources. The use of the open-source tool LangChain was suggested due to its extensive capabilities, including support for multi-agent systems. Five agents proposed answers, and an assessor agent, considering the evaluation of each answer along with the given requirements and provided knowledge, presented the final answer. This was then evaluated by project members. A total of three iterations were conducted, and in the third iteration, the average rating exceeded the threshold of eight.

The proposed by the model solution to a problem focused largely on creating technological (both software and hardware) building blocks that could be utilized by products and services from diverse portfolios. Given that these products and services targeted different markets with varying price points, different variants were proposed, ranging from the most feature-rich to the least feature-rich versions. This approach allowed the most complex variant (worst-case scenario from an approval perspective) to be tested during agency approval processes, thereby streamlining subsequent work on the other variants.

This solution enabled engineers to concentrate on building these building blocks by considering the requirements of the other variants, instead of switching between different technological projects. It also enhanced the flow of knowledge, both among engineers and between product managers. It is currently estimated that the Time-To-Market for new products will improve by at least twofold. The use of this solution also encouraged the team to apply it again in later stages of developing the discussed building blocks.

5. Conclusions

This study explores the integration of Generative Artificial Intelligence (GenAI) solutions in product management enhanced by the knowledge management framework. Drawing from the case study from the manufacturing sector, this has highlighted four key insights: 1. The influence of experimental approaches on the processes of assessing the business value of GenAI solutions, 2. The benefit of incorporating external expertise in the integration of advanced AI solutions during the product management process, 3. The impact of external experts on improving internal knowledge management processes and determining the maturity of these processes, and 4. The importance of having team members with diverse competency profiles, including T-shaped, Pi-shaped, and M-shaped skills.

Involving external experts, such as academic representatives, in the integration process of GenAI solutions can bring fresh perspectives and innovative (experimental) methods. This collaboration can enhance and simplify the development of the model and addresses competency gaps within the organization. Also, effective knowledge management is beneficial for the successful integration of GenAI. Practitioners should focus on developing and refining knowledge management processes, employing methods for capturing, organizing, storing, and sharing knowledge. Using frameworks like CLIMB can help assess and improve organizational maturity in this area. Having team members with diverse competency profiles (T-shaped, Pi-shaped, and M-shaped skills) is essential for the successful implementation and management of GenAI solutions. Organizations should invest in developing these competencies across their teams to ensure a well-rounded and effective integration process.

Future research should focus on the long-term impact of GenAI integration in product management, examining how these solutions evolve over time and their sustained effects on business value and process efficiency. Also, comparative studies across different industries can provide insights into how GenAI solutions can be tailored and optimized for specific sectors, highlighting unique challenges and opportunities.

References

Abadi, A.N., Nayeem, M.T., Rafiei, D., 2023. Product Entity Matching via Tabular Data. Presented at the International Conference on Information and Knowledge Management, Proceedings, pp. 4215–4219. https://doi.org/10.1145/3583780.3615172

Bandi, A., Adapa, P.V.S.R., Kuchi, Y.E.V.P.K., 2023. The Power of Generative AI: A Review of Requirements, Models, Input–Output Formats, Evaluation Metrics, and Challenges. Future Internet 15. https://doi.org/10.3390/fi15080260

Benham, N., Gao, S., Ng, Y.-K., 2022. A Hybrid Approach for Summarizing User Reviews Based on KL-Divergence and Deep Learning. Presented at the Proceedings - International Conference on Tools with Artificial Intelligence, ICTAI, pp. 325–333. https://doi.org/10.1109/ICTAI56018.2022.00054

Bosch, J., Olsson, H.H., Crnkovic, I., 2018. It takes three to tango: Requirement, outcome/data, and AI driven development. Presented at the Workshop on Software-intensive Business.

Bouschery, S.G., Blazevic, V., Piller, F.T., 2023. Augmenting human innovation teams with artificial intelligence: Exploring transformer-based language models. Journal of Product Innovation Management 40, 139–153. https://doi.org/10.1111/jpim.12656

Bulut, A., Mahmoud, A., 2023. Generating Campaign Ads & Keywords for Programmatic Advertising. IEEE Access 11, 43557–43565. https://doi.org/10.1109/ACCESS.2023.3269505

Choi, W., Jang, S., Kim, H.Y., Lee, Y., Lee, S.-G., Lee, H., Park, S., 2023. Developing an AI-based automated fashion design system: reflecting the work process of fashion designers. Fashion and Textiles 10. https://doi.org/10.1186/s40691-023-00360-w

Chong, M.J., Forsyth, D., 2020. Effectively unbiased FID and inception score and where to find them. Presented at the Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 6069–6078. https://doi.org/10.1109/CVPR42600.2020.00611

Colado, I.J.P., Colado, V.M.P., Morata, A.C., Píriz, R.S.C., Manjón, B.F., 2023. Using New AI-Driven Techniques to Ease Serious Games Authoring. Presented at the Proceedings - Frontiers in Education Conference, FIE. https://doi.org/10.1109/FIE58773.2023.10343021

Daugherty, P.R., Wilson, H.J., Narain, K., 2023. Generative AI Will Enhance — Not Erase — Customer Service Jobs. Harvard Business Review.

Deng, Z.G., Lv, J., Liu, X., Hou, Y.K., 2023. Bionic Design Model for Co-creative Product Innovation Based on Deep Generative and BID. International Journal of Computational Intelligence Systems 16. https://doi.org/10.1007/s44196-023-00187-9

Dorri, A., Kanhere, S.S., Jurdak, R., 2018. Multi-Agent Systems: A Survey. IEEE Access 6, 28573–28593. https://doi.org/10.1109/ACCESS.2018.2831228

Gupta, S., Sharma, P., Chaudhary, S., Kumar, V., Singh, S.P., Lourens, M., Beri, N., 2024. Study on the Beneficial Impacts and Ethical Dimensions of Generative AI in Software Product Management. International Journal of Intelligent Systems and Applications in Engineering 12, 251–264.

Gurkan, H., de Véricourt, F., 2022. Contracting, Pricing, and Data Collection Under the AI Flywheel Effect. Management Science 68, 8791–8808. https://doi.org/10.1287/mnsc.2022.4333

Kalam, K.T., Rahman, J.M., Islam, M.R., Dewan, S.M.R., 2024. ChatGPT and mental health: Friends or foes? Health Science Reports 7. https://doi.org/10.1002/hsr2.1912

Kanbach, D.K., Heiduk, L., Blueher, G., Schreiter, M., Lahmann, A., 2024. The GenAI is out of the bottle: generative artificial intelligence from a business model innovation perspective. Rev Manag Sci 18, 1189–1220. https://doi.org/10.1007/s11846-023-00696-z

Kulkarni, Akshay, Shivananda, A., Kulkarni, Anoosh, Gudivada, D., 2023. LLMs for Enterprise and LLMOps, in: Kulkarni, Akshay, Shivananda, A., Kulkarni, Anoosh, Gudivada, D. (Eds.), Applied Generative AI for Beginners: Practical Knowledge on Diffusion Models, ChatGPT, and Other LLMs. Apress, Berkeley, CA, pp. 117–154. https://doi.org/10.1007/978-1-4842-9994-4_7

Li, H., Wang, J., Lu, Y., Zhu, H., Ma, J., 2023. Chinese Multicategory Sentiment of E-Commerce Analysis Based on Deep Learning. Electronics (Switzerland) 12. https://doi.org/10.3390/electronics12204259

McKinsey, 2021. Global survey: The state of AI in 2021 | McKinsey, https://www.mckinsey.com/capabilities/quantumblack/our-insights/global-survey-the-state-of-ai-in-2021 (accessed 29.03.24).

Morizet, N., Desforges, P., Geissler, C., Pahon, E., Jemei, S., Hissel, D., 2023. Time to market reduction for hydrogen fuel cell stacks using Generative Adversarial Networks. Journal of Power Sources 579. https://doi.org/10.1016/j.jpowsour.2023.233286

Niemir, M., Mrugalska, B., 2023. Data Science Challenges of Automated Quality Verification Process in Product Data Catalogues. Presented at the Materials Research Proceedings, pp. 390–399. https://doi.org/10.21741/9781644902691-45

Ooi, K.-B., Tan, G.W.-H., Al-Emran, M., Al-Sharafi, M.A., Capatina, A., Chakraborty, A., Dwivedi, Y.K., Huang, T.-L., Kar, A.K., Lee, V.-H., Loh, X.-M., Micu, A., Mikalef, P., Mogaji, E., Pandey, N., Raman, R., Rana, N.P., Sarker, P., Sharma, A., Teng, C.-I., Wamba, S.F., Wong, L.-W., 2023. The Potential of Generative Artificial Intelligence Across Disciplines: Perspectives and Future Directions. Journal of Computer Information Systems 0, 1–32. https://doi.org/10.1080/08874417.2023.2261010

Parida, V., Sjödin, D.R., Wincent, J., Kohtamäki, M., 2014. Mastering the transition to product-service provision: Insights into business models, Learning activities, and capabilities. Research Technology Management 57, 44–52. https://doi.org/10.5437/08956308X5703227

Peffers, K., Tuunanen, T., Gengler, C.E., Rossi, M., Hui, W., Virtanen, V., Bragge, J., 2006. The Design Science Research Process: A Model for Producing and Presenting Information Systems Research, in: DESRIST International Conference on Design Science Research in Information Systems and Technology, Claremont, CA, USA, February 24-25, 2006. pp. 83–106.

Peng, X., Xintong, B., 2022. An effective strategy for multi-modal fake news detection. Multimedia Tools and Applications 81, 13799–13822. https://doi.org/10.1007/s11042-022-12290-8

Porter, M.E., Heppelmann, J.E., 2015. How Smart, Connected Products Are Transforming Companies. Harvard Business Review 31.

Przegalinska, A., Jemielniak, D., 2023. Strategizing AI in Business and Education: Emerging Technologies and Business Strategy, Elements in Business Strategy. Cambridge University Press, Cambridge. https://doi.org/10.1017/9781009243520

Reznikov, R., 2024. LEVERAGING GENERATIVE AI: STRATEGIC ADOPTION PATTERNS FOR ENTERPRISES. https://doi.org/10.2139/ssrn.4851632

Rossi, M., Terzi, S., 2017. CLIMB: maturity assessment model for design and engineering processes. International Journal of Product Lifecycle Management 10, 20–43. https://doi.org/10.1504/IJPLM.2017.082998

Sai, P.T., Sri, G.H., Lakshmi Surekha, T., 2023. Extraction of Emojis and Texts to Intensify Opinion Mining using Machine Learning and Deep Learning Models. Presented at the 2nd International Conference on Automation, Computing and Renewable Systems, ICACRS 2023 - Proceedings, pp. 829–837. https://doi.org/10.1109/ICACRS58579.2023.10404790

Samuelson, P., 2023. Generative AI meets copyright: Ongoing lawsuits could affect everyone who uses generative AI. Science 381, 158–161. https://doi.org/10.1126/science.adi0656

Shamshirband, S., Anuar, N.B., Kiah, M.L.M., Patel, A., 2013. An appraisal and design of a multi-agent system based cooperative wireless intrusion detection computational intelligence technique. Engineering Applications of Artificial Intelligence 26, 2105–2127. https://doi.org/10.1016/j.engappai.2013.04.010

Shi, C., Liang, P., Wu, Y., Zhan, T., Jin, Z., 2024. Maximizing user experience with LLMOps-driven personalized recommendation systems. ACE 64, 101–107. https://doi.org/10.54254/2755-2721/64/20241353

Smith, D.J., 2013. Power-by-the-hour: The role of technology in reshaping business strategy at Rolls-Royce. Technology Analysis and Strategic Management 25, 987–1007. https://doi.org/10.1080/09537325.2013.823147

Soltani-Fesaghandis, G., 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, 847–864. https://doi.org/10.22434/IFAMR2017.0033

Sun, X., Holm, H., Molavipour, S., Gebre, F.G., Pawar, Y., Radnosrati, K., Shalmashi, S., 2023. Recommendation System for Product Test Failures Using BERT. Presented at the International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management, IC3K - Proceedings, pp. 206–213. https://doi.org/10.5220/0012160800003598

Van Bossuyt, D.L., Hale, B., Arlitt, R., Papakonstantinou, N., 2023. Zero-Trust for the System Design Lifecycle. Journal of Computing and Information Science in Engineering 23. https://doi.org/10.1115/1.4062597

Wang, J., Liu, Y.-L., 2023. Deep learning-based social media mining for user experience analysis: A case study of smart home products. Technology in Society 73. https://doi.org/10.1016/j.techsoc.2023.102220

Wodecki, A., 2023. A Cross-Disciplinary Knowledge Management Framework for Artificial Intelligence in Business Projects. ECKM 24, 1471–1480. https://doi.org/10.34190/eckm.24.2.1371

Zhang, W., Zhang, J., Zhao, T., Tong, W., 2023. A color style fusion design method based on generative adversarial networks. Presented at the Proceedings - 2023 3rd International Conference on Frontiers of Electronics, Information and Computation Technologies, ICFEICT 2023, pp. 338–343. https://doi.org/10.1109/ICFEICT59519.2023.00063