

Artificial Intelligence in Product Development: Perspectives from Academia and Industry

Jan Henke^{1,2}, Elias Berger^{1,2}, Jochen Weippert², Kristin Paetzold-Byhain¹

¹ Chair of Virtual Product Development, Dresden University of Technology

² MAN Truck & Bus SE

Abstract: Artificial intelligence is increasingly discussed as a transformative technology in product development, yet its industrial adoption remains uneven. This study examines how academic and industrial experts perceive its applications, limitations and needs for action. Based on a qualitative survey of 26 participants, responses were systematically coded and clustered. The results reveal a partial divergence in perceived application areas. While both groups highlight data analysis, decision support and design automation, academia places stronger emphasis on simulation and modelling, whereas industry prioritizes knowledge management, routine automation and quality assurance. Despite these differences, both groups converge on key barriers, particularly data availability and quality, user trust, hallucinations and integration into existing toolchains. Several industrial participants report no active usage of artificial intelligence, indicating an implementation gap between research and practice. Overall, artificial intelligence in product development is currently positioned primarily as an efficiency-enhancing support tool rather than an autonomous design agent.

Keywords: Artificial Intelligence, Product Development, Engineering Design, Survey

1 Introduction

Product development (PD) plays a crucial role in sustaining long-term competitiveness in industry (Morgan et al., 2019). At the same time, PD organizations are confronted with intensifying challenges such as growing global competition, shortened development cycles and increasing product complexity (Lindemann et al., 2009; Vogel and Lasch, 2018). These conditions require companies to continuously improve efficiency, quality and innovation capability throughout the PD process. Artificial intelligence (AI) has long been discussed as an auspicious enabler to address these challenges in PD (Berger et al., 2025; Song et al., 2022). AI-based methods offer the potential to support or automate cognitive engineering tasks, enhance decision-making under uncertainty and assist technical designers in activities such as requirements analysis, ideation, concept generation, simulation and process planning (Gyory et al., 2022; Lu et al., 2012; Salehi and Burgueño, 2018). Recent innovations regarding computational infrastructure, large-scale datasets (Radford et al., 2019), as well as the advent of highly effective deep learning architectures (Vaswani et al., 2017) have significantly expanded the technical feasibility of AI applications across domains such as consumer services, neuroscience and logistics (Jordan and Mitchell, 2015; Vieira et al., 2017). However, the extent to which these advances have translated into tangible and scalable benefits for industrial PD remains an open question. In recent years, academic research has proposed a wide range of AI use cases across the PD process, ranging from early-stage design support to downstream engineering and manufacturing activities (Wuest et al., 2016; Yüksel et al., 2023). While individual case studies and prototype systems demonstrate promising results, the overall picture of AI adoption in PD, taking both an academic and an industrial point of view into account, is unclear. The lack of systematic comparison of applications, expectations and limitations across stakeholder groups, causes limited clarity regarding how researchers and practitioners in PD perceive, use and prioritize AI methods. This study addresses this gap by presenting a survey-based socio-technical investigation of AI adoption in PD from both academic and industrial viewpoints. The survey comprises five open-ended questions targeting perceived application areas, current projects, estimated gaps, challenges and strategic needs. It was completed by 26 experts, which includes nine academics specialized in PD from different German universities, as well as 17 employees, comprising twelve engineers and five managers, from the engineering business area of MAN Truck & Bus SE. By contrasting these perspectives, this study aims to provide an empirical snapshot of the current state of AI in PD identifying shared assumptions as well as critical mismatches and perception gaps between research and industrial practice. The central research question guiding this work is:

How do academic and industrial experts perceive the applications, limitations, challenges and needs for action of artificial intelligence in product development?

By answering this question, this paper contributes empirical evidence to the ongoing discussion on AI-assisted PD. The findings aim to inform future research directions, support the alignment of academic methods with industrial needs and provide design researchers and practitioners with a clearer understanding of how AI is currently shaping PD, and how it is expected to shape this area in the future.

2 Background

2.1 Product development

PD is a central element of the product lifecycle and encompasses the organizational units, methods, tools and processes involved in transforming market needs regarding function, quality, costs and design into technical product solutions (Ponn and Lindemann, 2011). The PD process can be understood as a structured information-processing activity in which customer requirements are iteratively translated into product architectures, detailed designs and manufacturing-relevant information. This iterative fashion impedes the planning and structuring of PD making systematic development processes, which guide the course of action of the involved individuals and teams, a necessity in order to develop successful products (Ponn and Lindemann, 2011). Furthermore, during PD the entire product life cycle should be taken into consideration (Blessing and Chakrabarti, 2009). Within engineering design research, PD is commonly described as a socio-technical system in which formalized processes, digital tools and human actors interact (Blessing and Chakrabarti, 2009). Digital engineering methods and computational tools have increasingly shaped the PD process by facilitating engineering tasks such as modelling, simulation, optimization and collaboration (Bickel et al., 2019). Despite a high degree of digitalization, PD remains strongly human-centred. Individual expertise and experience, domain knowledge, creativity as well as social and communication skills continue to play a decisive role in design quality and project success (Ponn and Lindemann, 2011). Therefore, new virtual tools and computational methods introduced into PD must not only be technically effective but also compatible with existing workflows, roles and organizational structures.

2.2 Artificial intelligence in product development

AI refers to a broad class of computational methods that enable machines to perform tasks typically associated with human intelligence, such as perception, learning, reasoning and decision-making (Russell and Norvig, 2022). Machine learning is a crucial subsection in the overall field of AI and is characterized by the fact that machine learning systems are primarily trained on data, and not explicitly programmed, finding a statistical structure in the process (Chollet, 2026). Generative AI (GenAI), based on deep learning architectures such as generative adversarial networks (Goodfellow et al., 2014), transformers (Vaswani et al., 2017), diffusion models (Sohl-Dickstein et al., 2015) and variational autoencoders (Kingma and Welling, 2022), represents a recently established subset of these methods with particular relevance for creative and knowledge-intensive design activities. These methods aim to create new, high-quality data samples that closely mimic the training data distribution (Bond-Taylor et al., 2021). In the context of PD, AI methods have been investigated for several decades, including expert systems (Rao et al., 1999), knowledge-based engineering (Kügler et al., 2023) and more recently data-driven machine learning approaches (Shabestari et al., 2019; Wang et al., 2022). Recent advances in machine learning, particularly deep learning, have significantly expanded the scope of potential AI applications in PD. These include tasks such as requirements engineering, information retrieval, knowledge management, design space exploration, code generation, performance prediction and anomaly detection (Afifi et al., 2025; Kretzschmar et al., 2024a). From a systems perspective, AI in PD does not exist as an isolated algorithm but as part of a broader socio-technical ecosystem. An effective AI-assisted PD system requires the integration of data acquisition and preprocessing pipelines, algorithmic models, user interfaces and organizational processes. Therefore, the value of AI in PD is shaped not only by technical performance but also by factors such as data availability, explainability, trust and alignment with the daily practices of the involved engineers (Chen et al., 2025; Ma et al., 2024).

2.3 Related surveys on artificial intelligence in product development

Several recent studies have investigated the role of AI in engineering design and PD using survey- or interview-based approaches. These works provide valuable insights into current practices, expectations and challenges. The survey-based study of Edgecomb et al., 2025 presents industrial perspectives on AI in engineering design across different roles and domains highlighting perceived benefits, application areas as well as adoption barriers. The results indicate strong awareness regarding AI-supported engineering tasks, while also identifying data security and intellectual property issues as the main limiting factors. The survey of Steininger et al., 2024 concentrates on the current and potential usage of AI in early PD phases, as well as challenging factors. It underlines the gap between the potential of theoretical methods and their operational deployment, illustrated on the example of BMW's engineering department. The study of Gomez et al., 2025 presents the role of GenAI in the development of design automation systems for complex products. It encompasses a survey examining the understanding of a conceptual model developed for visualizing the contributions of large language models to design tasks in order to leverage their new orchestration capabilities in engineering design, which was presented to employees of GKN Aerospace and MAN Truck & Bus SE. Beyond these contributions, several review and survey papers have addressed AI in design more broadly, often focusing on technical capabilities rather than stakeholder perceptions (Berger et al., 2026; Afifi et al., 2025; Berger et al., 2024; Kretzschmar et al., 2024b; Wang et al., 2022; Shabestari et al., 2019). Overall, existing surveys tend to focus either on academic perspectives, high-level industrial trends or specific PD subfields. Comparative empirical studies that directly contrast academic and industrial viewpoints within the holistic PD domain remain limited. The present study builds on this body of work by providing a targeted survey of AI in PD that explicitly contrasts perspectives from academic research and industrial practice.

3 Research methodology

In contrast to literature-based analyses of AI in PD, this study follows an exploratory qualitative research design to capture and compare expert perspectives on the topic. A thematic coding procedure was applied to systematically structure the open-ended survey responses following established qualitative content analysis practices (Schreier, 2012). Coding was conducted independently by two researchers using a shared Excel-based coding matrix. An initial open screening of the responses was conducted to identify recurring themes in an inductive manner. Based on these emergent patterns, a structured codebook with operational definitions and inclusion criteria was developed and refined through joint discussion. This codebook was subsequently applied deductively to the entire dataset to ensure systematic and consistent coding. The coding was performed at the level of semantic response segments, allowing multiple codes to be assigned to a single statement where appropriate. After independent coding, discrepancies were reviewed and resolved through consensus, resulting in a harmonized coding matrix. The process pipeline of our research approach can be seen in Figure 1.

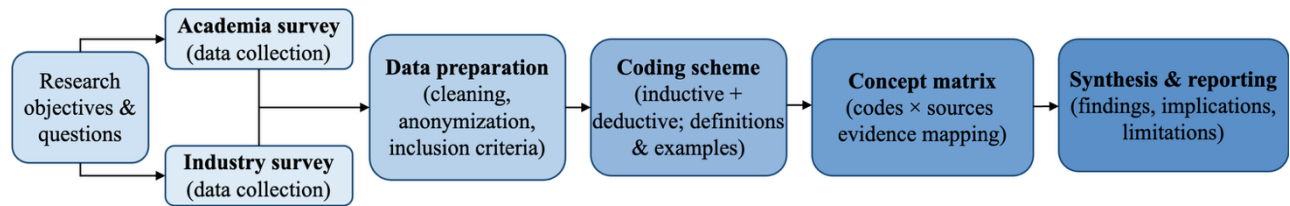


Figure 1. Process chart of our research approach

The survey, which acts as the base of this study, contains five questions about AI and its applications, limitations, challenges and needs for action in regard to PD. These questions are listed below:

1. *Where do you currently see useful applications of artificial intelligence methods in product development?*
2. *What are typical projects and tasks in product development, where you develop solutions using artificial intelligence?*
3. *Which tasks in product development cannot be solved or supported using artificial intelligence at this point?*
4. *Which challenges do you see regarding the usage of artificial intelligence methods in the context of product development?*
5. *Which needs for action do you see for applying artificial intelligence methods efficiently in product development?*

This question catalogue was sent to 30 professors from German universities, with nine of these responding to the questions. Academic participants were selected because they actively conduct research in PD and are therefore expected to be familiar with methodological and technological developments in the field. Furthermore, the same questionnaire was sent to 112 employees of the engineering business unit of MAN Truck & Bus SE, from which twelve engineers and five managers responded. The industrial participants were drawn from a large German truck manufacturer to represent a mature engineering organization with established PD processes. Therefore, 26 answers were collected in total, representing both academic and industrial perspectives, including engineering and managerial roles. Although this sample size does not allow for statistical generalization, it is sufficient for exploratory qualitative pattern identification (Guest et al., 2006). To enable higher-level interpretation, individual codes were consolidated into broader thematic clusters separately for each question. The coded dataset was subsequently arranged into a concept matrix following established cross-case data display methods (Miles et al., 2014), linking themes to response sources and enabling systematic comparison across participants. This structured coding and clustering procedure formed the analytical basis for the thematic synthesis reported in the results section below.

4 Results

During the review of the survey responses, answer categories were iteratively established for each question to enable distinct clustering of answers, which can be seen in Table 1, Table 2, Table 3, Table 4 and Table 5.

4.1 Perceived application areas of artificial intelligence in product development

The answers to question 1 and question 2 allow for a description of application areas of AI in PD that are perceived as useful, as well as typical projects and tasks in PD, where solutions are developed using AI.

Table 1. Clusters and examples for answers to question 1

Inductive cluster	Answer examples
<i>Data analysis & decision support (DAT)</i>	• Pattern recognition in image and speech • Analysis of vehicle and sales data

<i>Design automation, configuration automation & requirements management (DAR)</i>	• Generative design of component variants based on historical data • Design optimisation and exploration of solution spaces • Automated generation or plausibility check of bill of materials • Comparison between requirements and solutions from the product portfolio
<i>Quality assurance & fault detection (QAF)</i>	• Image processing for fault detection
<i>Reporting (REP)</i>	• Writing protocols and generation of PowerPoint-slides
<i>Project management (PRJ)</i>	• Evaluation of historical project data for generation of future schedules • Cost estimation and risk analysis
<i>Knowledge management (KNO)</i>	• Restructuring of big datasets via prompts • Market, trend- and technology analysis
<i>System integration (SYS)</i>	• Reduction of isolated applications • Development of user-friendly applications
<i>Programming (PRG)</i>	
<i>Translation & transcription (TRN)</i>	• Bridging cultural differences and language barriers • Automated translation of lecture recordings
<i>Human resources applications (HRA)</i>	• Review of applications
<i>Teaching (TEA)</i>	• Usage of AI-generated content as basis for discussions with students

From the heatmap shown in Figure 2 it can be seen that *data analysis & decision support* as well as *design automation, configuration automation & requirements management* are the application areas that are mentioned the most. Both stakeholder groups assigned comparable relevance to these clusters, suggesting a shared understanding of AI's primary operational value. *Reporting, knowledge management, project management* and *quality assurance & fault detection* are perceived as secondary rather than core AI use cases in PD. For *knowledge management* and *quality assurance & fault detection* industry respondents attribute comparatively greater relevance. *Translation & transcription* and *system integration* are mentioned rarely, while *human resources applications, teaching* and *programming* are only mentioned one time each indicating that these application areas are of less interest.

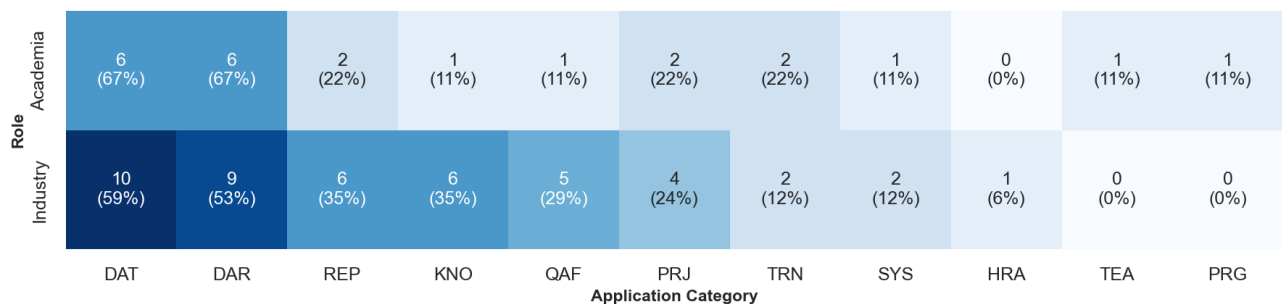


Figure 2. Heatmap showcasing clustered answers of different stakeholder groups to question 1

Table 2. Clusters and examples for answers to question 2

Inductive cluster	Answer examples
<i>Data analysis & decision support (DAT)</i>	• Multiparameter optimisation for interdisciplinary PD • Anomaly detection and fault prognosis
<i>Requirements management (REQ)</i>	• Generation of specification sheets
<i>Ideation (IDE)</i>	• Brainstorming support
<i>Simulation & modelling (SIM)</i>	• Usage of AI tools for FE (finite elements) optimisation of parts and components
<i>Text processing (TXT)</i>	• Generation of evaluations and product documentation
<i>Image generation (IMG)</i>	
<i>Knowledge management (KNO)</i>	• Patent and literature search • Querying methods for finding existing solutions in the product catalogue
<i>Programming (PRG)</i>	• VBA (visual basic for applications)

<i>Teaching (TEA)</i>	• Generation of exam questions and teaching documents in all languages
<i>No usage (NON)</i>	

The heatmap in Figure 3 shows that *data analysis & decision support* and *simulation & modelling* are the most mentioned tasks, where the survey participants, particularly from the academic side, develop solutions using AI. These two clusters are closely followed by *text processing* tasks, which are mentioned often by the industrial experts. *Knowledge management* has been mentioned occasionally by both the academic as well as the industrial survey participants. On the other hand, six practitioners from industry reported *no usage* while none of the academic researchers did. *Programming* and *requirements management* are more rarely contemplated by both sides. *Image generation* and *ideation* tasks are also mentioned infrequently, but only from the industrial experts. Furthermore, one professor names *teaching* as an AI-assisted task.

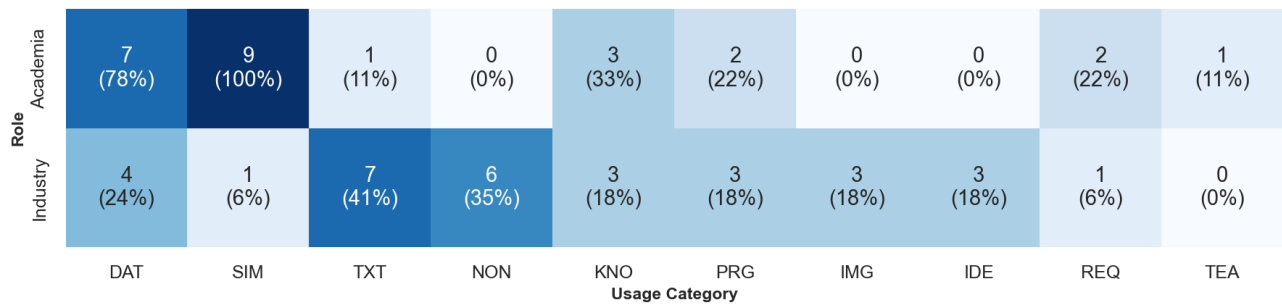


Figure 3. Heatmap showcasing clustered answers of different stakeholder groups to question 2

4.2 Perceived limitations of artificial intelligence in product development

While the previous section highlights perceived application potential, the following section outlines tasks that stakeholders currently consider unsuitable for AI support.

Table 1. Clusters and examples for answers to question 3

Inductive cluster	Answer examples
<i>Data analysis & pattern recognition (DPR)</i>	Analysis of historical orders and country-specific configuration packages
<i>Decision making (DEC)</i>	- Making responsible decisions with ethical, legal and safety-critical implications - Making gut feeling decisions and subjective or aesthetic assessments
<i>Ideation, design automation, configuration automation & requirements management (IDA)</i>	- Development of completely new concepts and technologies - Development of solutions based on multiple parameters - CAD - Variant management - Generation of bill of materials
<i>Quality assurance & fault detection (QAF)</i>	Comparison of trend data of vehicle utilisation to investigate wearing behaviour
<i>Reporting (REP)</i>	Regulatory proofs
<i>Project management (PRJ)</i>	- Generate target objectives and definitions - Estimation of project schedules
<i>Knowledge management (KNO)</i>	Clarification of existing solutions
<i>Methodological & reproducible solution finding (MRS)</i>	- Solution finding via methodological approaches - Development of physical behavioural models - Development of equation systems and performance of logical operations
<i>Cross-functional communication (CFC)</i>	- Considering parameters over several departments (e.g., R&D and sales) - Interpreting cultural nuances
<i>Tasks, for which not enough data or explicit knowledge is available (NDK)</i>	
<i>Acquisition & care of customers (CUS)</i>	Defusing escalating situations (e.g., explain delivery delays to customers)

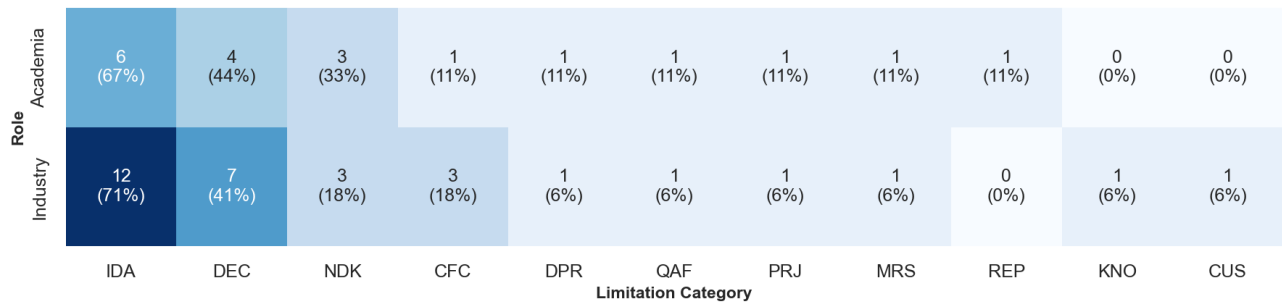


Figure 4. Heatmap showcasing clustered answers of different stakeholder groups to question 3

The plot in Figure 4 shows the received feedback regarding the currently perceived limitations of AI in PD. The most mentioned category of PD tasks, that cannot be solved or supported through AI, is *ideation, design automation, configuration automation & requirements management*. Both academic and industrial experts agree on this point. Another limitation cluster, which is frequently named from both sides, is *decision making*. A more general category of limited tasks is *tasks, for which not enough data or explicit knowledge is available* which has been mentioned occasionally from academic and industrial survey participants. *Cross-functional communication* has more rarely been referred to as a task, which cannot be solved or supported via AI. Furthermore, very sporadically mentioned categories are *data analysis & pattern recognition, quality assurance & fault detection, project management, methodological & reproducible solution finding, reporting, knowledge management and acquisition & care of customers*.

4.3 Perceived challenges of artificial intelligence adoption in product development

Question 4 examines challenges regarding the adoption of AI methods in PD. The received answers are categorized into four different clusters based on the taxonomy of challenges of Berger et al., 2026.

Table 4. Clusters and examples for answers to question 4

Inductive cluster	Answer examples
<i>Data-related challenges</i>	• Data availability and quality • Bias in training data • Data security and privacy
<i>Model-related challenges</i>	• Lacking originality and innovation of new solutions • Insufficient theoretical methods for tackling complexity of practical problems
<i>Integration-related challenges</i>	• Insufficient interfaces and connection between tools • Lacking expertise of employees • Effective selection of use cases that create measurable value • Insufficient description of AI methods in scientific publications • Missing standards, blueprints and best practices
<i>Socio-technical challenges</i>	• Lack of critical questioning of AI-generated results • Lacking reproducibility and explainability of AI-generated solutions • Deskilling and overreliance • Lacking trust of users and job security anxiety • Lacking soft skills of AI

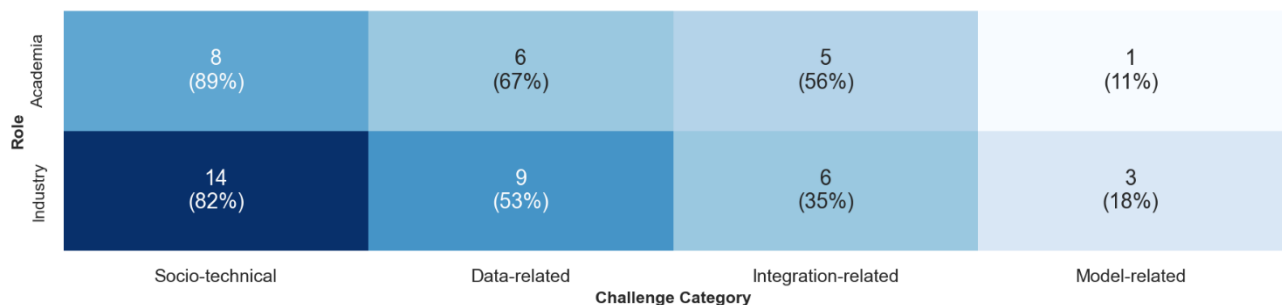


Figure 5. Heatmap showcasing clustered answers of different stakeholder groups to question 4

Figure 5 demonstrates that *socio-technical challenges* such as deskilling, job security anxiety, missing trust of users as well as lack of critical evaluation of AI-generated content are mentioned the most, especially from the industrial perspective. *Data-related challenges*, e.g., insufficient availability, quality or security of data, are mentioned frequently by industrial practitioners and academics. *Integration-related challenges* such as insufficient interfaces and connection between tools and lacking expertise of stakeholders are cited as important challenges from both sides as well. On the other hand, *model-related challenges* like missing originality and innovation of AI-generated solutions are of minor importance to both industry and academic experts.

4.4 Perceived needs for action of artificial intelligence in product development

Question 5 aimed to identify the actions required for the efficient deployment of AI methods in PD tasks. Similarly to question 4, the perceived needs for action are categorized into data-related, model-related, integration-related and socio-technical-related answers based on Berger et al., 2026.

Table 5. Clusters and examples for answers to question 5

Inductive cluster	Answer examples
<i>Data-related needs for action</i>	• Cross-functional and interdepartmental integration of data • Generation and sharing of realistic datasets for research • Ensuring data security, responsible usage and data sovereignty in the company
<i>Model-related needs for action</i>	• Development of reliable methods for validation of AI-generated results • Implementation of uniform criteria for the evaluation of AI • Standardisation of AI systems
<i>Integration-related needs for action</i>	• Training of employees to reduce knowledge gaps and retention towards AI • Selection of useful AI use cases with concrete and measurable value • Make long-term investments in AI • Ensuring fast implementation and subsequent scaling of AI pilot projects
<i>Socio-technical-related needs for action</i>	• Taking socio-technical factors like job loss and sustainability into account • Usage of AI for decision support instead of fully automated decision making • Create interdisciplinary teams combining domain knowledge with AI expertise

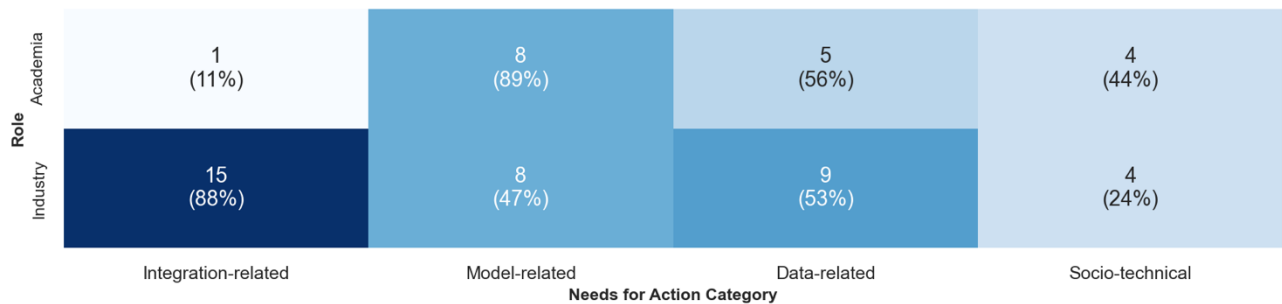


Figure 6. Heatmap showcasing clustered answers of different stakeholder groups to question 5

From Figure 6, it is evident that model-related needs for action like developing methods for validation of answers, standardization of AI systems and uniform evaluation criteria are of critical importance to both industrial and academic experts. Similarly important are integration-related needs for action such as educating employees and effectively selecting high-value AI use cases. These are particularly relevant to the stakeholders from industry. Slightly less important but still significant are data-related needs for action. While industrial practitioners emphasize cross-functional integration of data, the academic survey participants tend to focus on the creation and subsequent sharing of realistic datasets for research. The least mentioned category is socio-technical-related needs for action where the development of interdisciplinary teams combining domain knowledge with AI expertise was mentioned the most, particularly from the academic participants.

5 Discussion

Based on the presented results, conclusions regarding the present maturity of AI in PD can be drawn. Currently, in the context of PD, AI is perceived as an analytical and decision-support tool aiming to enhance efficiency with further important application areas being design and configuration automation as well as simulation and modelling. An interesting

difference between the surveyed stakeholder groups is that while all academic participants report tasks and projects, where they rely on AI to develop solutions, a significant portion of the industrial participants reports no usage at all. This pattern suggests the presence of an implementation gap, potentially rooted in persisting knowledge gaps or organizational barriers in industry. Another explanation is that while in industry oftentimes an operational caution is dominating, research environments tend to embrace experimentation. Interestingly, while design and configuration automation is among the most frequently perceived application areas, it is also the most frequently mentioned limitation. This points towards that stakeholders distinguish between incremental optimization tasks and truly creative or system-level design automation, which indicates a conceptual boundary in how AI's role in PD is understood. While AI is accepted as a tool for parametric optimization and variant exploration, it is not yet perceived as capable of genuine conceptual innovation or responsibility-bearing system design. Moreover, creative and high-responsibility decisions remain attributed to humans, and either can or should not be outsourced to AI. This suggests that AI maturity in PD is currently positioned at an operational-support level rather than a strategic or cognitive-substitution level. In general, there is a clear perception gap between potential and actual usage of AI in PD, particularly in industry. Socio-technical concerns are the dominant category of perceived challenges with model-related challenges being cited the least. The small importance given to model-related concerns contrasts recent insights from literature (Berger et al., 2026). A possible explanation is that industrial practitioners, who constituted the majority of survey participants, are more concerned with tangible socio-technical issues such as deskilling, overreliance, potential job loss, limited user trust and insufficient critical scrutiny of AI-generated outputs, rather than with underlying algorithmic limitations. Regarding necessary future initiatives to enable the efficient deployment of AI-methods in PD, model-related and integration-related needs for action are mentioned the most, highlighting that both theoretical and practical improvements are required for more widespread adoption of AI methods in PD.

5.1 Commonalities and differences between academia and industry

A comparison of the most frequent thematic clusters regarding AI applications in PD reveals a difference in emphasis between the academic and industry groups. Academia responses are dominated by *data analysis & decision support* and *simulation & modelling* indicating a stronger focus on AI as an enabler for technically complex workflows in PD. In contrast, the industry group prioritizes *text processing*, *image generation* and *ideation* tasks. Furthermore, *knowledge management* and *quality assurance & fault detection* are application areas of AI in PD perceived as useful by practitioners from industry. This suggests that immediate productivity gains through the automation of rather simple routine tasks as well as easy information access are perceived as the most valuable near-term applications. This divergence reflects different incentive systems with academia prioritizing methodological advancement for complex tasks, whereas industry emphasizes immediate productivity gains. An interesting difference is furthermore that several members of the industry group report *no usage* of AI methods, which does not hold true for any of the academic participants. Moreover, practitioners in this study attribute greater relevance to socio-technical and organizational factors, whereas the literature emphasizes algorithmic capability and model validity as primary bottlenecks (Berger et al., 2026). This reflects a perception gap between research discourse and industrial reality, which indicates that current AI research in PD may not fully address the immediate adoption constraints perceived in industrial environments.

5.2 Recommendations for researchers and practitioners

Based on the observed mismatches between academic and industrial priorities evident in the survey answers, several research directions emerge. First, research should place stronger emphasis on ensuring that AI methods can be adopted more widespread in PD by not only developing sophisticated algorithms, but also taking socio-technical factors, such as lack of explainability and user trust into account, which coincides with findings from the literature (Samek et al., 2017; Wang et al., 2022). A possible route would be to focus on hybrid approaches that combine data-driven models with rule-based checks, physics-based validation or constraint systems to reduce hallucinations and unreproducible outputs (Afifi et al., 2025). Second, there is a need for AI approaches that explicitly handle sparsity and bad quality of data as these constraints were highlighted by both groups, which aligns with insights from the literature (Afifi et al., 2025; Whang et al., 2021). Third, research should focus more on AI methods that can be integrated into real engineering toolchains, including CAD/PLM, requirements management tools and enterprise databases, rather than just assuming clean and centralized datasets to address the persisting integration-related challenges. Fourth, future work should evaluate AI systems not only by predictive accuracy but by socio-technical criteria such as usability, explainability, integration effort and measurable time savings in real PD workflows. So, in conclusion, future academic research should shift from purely algorithmic performance optimization toward system-level integration of AI into socio-technical engineering environments. The survey results suggest that industrial AI deployment in PD should follow an incremental and risk-aware adoption strategy. High-frequency, low-risk applications such as knowledge retrieval, translation and report generation represent promising entry points due to their immediate productivity benefits and comparatively low integration requirements. In parallel, organizations should establish a clear data strategy that improves accessibility, consistency and governance of engineering-relevant data sources, as data quality and fragmentation were frequently reported barriers. For safety-critical or regulatory-relevant use cases, AI should be introduced only with human-in-the-loop processes, traceability mechanisms and validation layers. Finally, the responses underline the importance of organizational capability building through training programs and the founding of interdisciplinary teams, which is essential to scale AI projects.

5.3 Limitations

This work provides a comparative snapshot of how academic and industrial experts perceive AI in PD. Given the exploratory nature of the study and the qualitative survey format, the findings are intended to support analytical generalization rather than statistical inference. The sample size ($n=26$) allows for first insights, but larger cohorts would allow stronger quantitative claims and finer-grained subgroup analyses. In addition, the industrial perspective is grounded in one company context, which may reflect organization-specific processes and tool landscapes. Furthermore, responses capture self-reported perceptions rather than direct observation of AI usage in practice, motivating complementary interview- and field-based studies. Moreover, this study did not measure the AI knowledge of the survey participants, so some of the differences observed between the stakeholder groups could be caused by varying AI familiarity levels instead of stakeholder-group membership. Finally, while coding was conducted independently by two researchers and consolidated through consensus, qualitative analysis inevitably involves interpretive judgment. Future work should therefore expand the study across multiple companies and domains and triangulate survey findings with longitudinal and observational data. Despite these limitations, this study contributes the first structured comparative perception analysis of AI in PD between academia and industry, an empirically grounded cluster taxonomy of AI application areas, barriers and needs and evidence indicating a socio-technical perception gap between research discourse and industrial reality.

6 Conclusion and outlook

This paper investigated how academic and industrial experts perceive the application areas, barriers and needs for action of AI in PD. The findings suggest that AI in PD is currently positioned primarily as an efficiency-enhancing support technology rather than as an autonomous creative agent. Besides data analysis, decision support and design automation, which are essential applications for both stakeholder groups, academia primarily associates AI's potential with complex workflows such as simulation and modelling tasks. In contrast, industry participants prioritize near-term productivity gains through knowledge management and routine automation. Despite these differing priorities, both groups converge on key adoption barriers, most notably trustworthiness of AI outputs in engineering contexts, integration into existing toolchains and data availability and quality. The findings contribute an empirical snapshot of AI perceptions in PD and highlight where expectations align and diverge between research and practice. The study reveals that the main bottlenecks of AI in PD are not perceived as algorithmic, but socio-technical making alignment between technical capability and socio-technical readiness decisive. Future work should broaden the sample across multiple industries and countries, refine the cluster taxonomy through additional qualitative interviews and investigate how AI adoption evolves over time as tool integration and governance mechanisms mature.

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