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ScienceDirect

Procedia CIRP 136 (2025) 171–176

www.elsevier.com/locate/procedia

35th CIRP Design 2025

The influence of AI support on product development results: A Live-Lab case study of a top-heat grill

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Abstract

This study examines the influence of AI tools on development speed, functionality, costs and team satisfaction in a university design project. Two engineering teams developed solutions for a top-heat grill within three development sprints. The test group used AI tools from the start, the control group from the third sprint onwards. The comparison, based on interviews and the evaluation from the software tools used, shows that the use of AI tools has a positive impact on development speed, functionality and costs. These findings support the understanding of the potential of AI tools in development projects.

Keywords: AI-driven design; development efficiency; engineering project management; Live-Lab

1. Introduction

In today's business environment, characterized by volatility, uncertainty, complexity, and ambiguity (VUCA), the expectations placed on companies and employees continue to rise. To thrive in this dynamic landscape, skills such as cognitive flexibility, agile thinking, intercultural competence, creativity, and complex problem-solving are becoming more essential than ever [1]. Artificial Intelligence (AI) is becoming increasingly important to effectively meet the challenges of the VUCA world. AI can increase the productivity of employees by automating recurring tasks, enabling well-founded decision-making, and thus increasing the efficiency of individual developers or even organizations [2]. At the same time, the utilization of AI tools can help to reduce costs, human error and eventually enhancing agility, which is essential in a rapidly changing environment [3]. An exemplary application of AI in product development is the specialized tool "*Optimate*", which optimizes sheet-metal designs to ensure accuracy and adherence to industry standards. By embedding expert knowledge, the tool conducts feasibility analyses focusing on manufacturability and offers detailed cost forecasts, streamlining the design review process. Additionally, *Optimate* identifies error-prone areas and suggests optimization strategies, delivering precise recommendations for enhancing sheet metal components and ensuring robust design quality. The potential of AI tools, particularly in product development, demonstrates multiple areas to support individual developers. To effectively assess the capabilities and the influence of AI in this domain, a suitable research environment is essential. Live-Labs offer an optimal solution to balance the controlled conditions of laboratory research with the practical applicability of field studies, allowing for real-world experimentation with a degree of control. This approach enables researchers to observe AI tools' performance and adaptability within authentic development scenarios, providing valuable insights into their practical effectiveness. The Generational Sheet-metal Development (GSD) Live-Lab offers an environment for advancing sheet-metal development, particularly by focusing on iterative improvements across product generations. This Live-Lab approach centers on the generational refinement of a sheet-metal top-heat grill, where each successive product generation benefits from optimizations based on insights from previous iterations [4].

10.1016/j.procir.2025.08.031

2. State of research

2.1. System Generation Engineering

In order to support the development of a technical system, the development process must be analyzed. In the model of System Generation Engineering (SGE), the process of developing a new generation of technical products or subsystems builds upon a foundational model known as the Reference Product or System. This Reference Product serves as the baseline for the development process, where an existing predecessor, a competitor's product, or a similar source that provides essential design insights and functional inspiration is utilized. By using the Reference Product as a starting point, SGE enables developers to incorporate proven design and functional components, guiding the enhancement and refinement of new system generations. The model of SGE incorporates three specific types of variation to develop the system of objectives. The Carryover Variation (CV) involves reusing components, modules, or features from the Reference Product that have proven effective, thereby ensuring reliability, and reducing the need for redesign. Interfaces of components are modified to ensure integrability in the system of objectives. With the Attribute Variation (AV), individual features or characteristics are modified to better align the new product generation with emerging needs, standards, or technologies, providing flexibility without altering the core structure. The Principle Variation (PV) involves making fundamental changes to the underlying principles or technologies, allowing for significant innovation and adaptation to new requirements or market demands. Through these variations, SGE facilitates a structured approach to continuous improvement, allowing each generation to benefit from cumulative insights from previous development activities, while also adapting to technological advancements. This model describes the balanced approach between preserving valuable design elements and introducing innovation in the industry [5,6].

2.2. Live-Lab GSD – Generational Sheet-metal Development

To examine how AI tools influence the sheet-metal design process, an appropriate research environment is essential. To support development activities of organizations in the industry, implementing new methods, processes, and tools often encounters practical limitations. These challenges frequently stem from a gap between anticipated and actual outcomes, as many methods and tools are initially developed in laboratory conditions of academic environments, with evaluations typically occurring in controlled lab studies or limited to specific industry cases. While laboratory studies offer high internal validity and simplified conditions, they often lack the complexity and unpredictability of real-world scenarios. Conversely, field studies capture practical realities more accurately but can yield results that are specific to certain environments, potentially limiting their broader applicability. Live-Labs aims to merge the advantages of a controlled environment of laboratory studies with the complexity of real-world development settings. A Live-Lab functions as a research space that replicates real development processes while preserving a high level of control over experimental variables. In these environments, participants are engaged as active developers rather than passive research subjects, enabling a comprehensive evaluation of factors such as user acceptance, practical applicability, or the integration of diverse methods to address design challenges [7].

The Live-Lab GSD, illustrated in Figure 1, is designed as a research environment embedded and employed in an academic course of the Hamburg University of Technology (TUHH) over a duration of four months. Here, GSD provides an environment to support iterative and agile validation of design methodologies for sheet-metal development within the model of SGE. GSD allows researchers to validate these methodologies in a realistic setting while maintaining control over experimental conditions. The development objective focuses on the iterative improvement of a top-heat gas grill utilizing previous grill generations as reference systems. GSD facilitates diverse studies such as reducing validation time through generational engineering and variation types, enhancing sustainable metal design, and exploring decision heuristics within agile development processes [4].

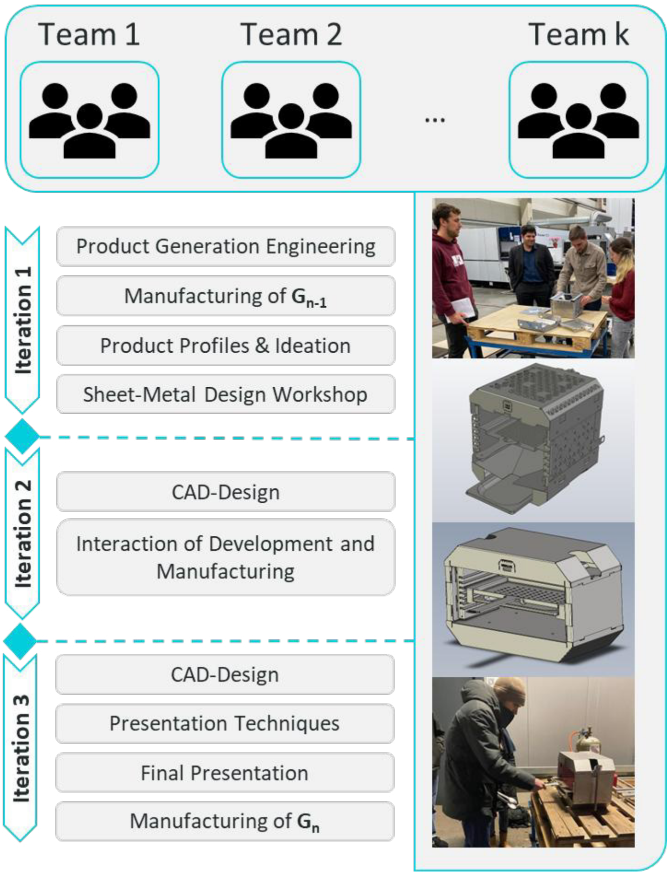

Figure 1. Live-Lab GSD - Generational Sheet-metal Development

2.3. Potential of AI tools in product development

The successful development of new generations of technical products depends on a comprehensive understanding of the market, the customer needs, the ability to incorporate gained knowledge from previous development activities as well as early validation into the product development process [8]. Given the increasing complexity in many industries, an effective product development process relies on cross-functional teams working closely together to create innovative and competitive products [9,10]. The integration of AI into the product development process offers great advantages to support individual engineers or teams, as it provides the possibility to support decision making in product design [11], enhance manufacturability by design error reduction [12], and accelerate prototyping of early design solutions [13]. This leads to more efficient and cost-effective development activities of new products [14].

A practical example of the successful use of AI can be found in sheet-metal design. The study by Ruey-Kai Sheu et al. shows how AI systems are used to identify different types of production-related defects in sheet metal-based products. The AI-supported automation of optical inspection proved to be a valuable extension of the production process, as it significantly increases the precision of defect detection and thus improves quality assurance [15]. Another example of AI tools specifically for sheet-metal design is provided with *Optimate* as an AI-supported platform developed for the optimization of sheet-metal design, focused on improving component geometry, reducing design errors, and minimizing manufacturing costs. Utilizing a specialized algorithm and machine learning techniques, *Optimate* systematically analyzes sheet-metal components to identify areas for potential material reduction and structural adjustments. This tool applies industry-standard design principles, including established guidelines and directives, to ensure compliance in the resulting optimized sheet-metal parts. By correcting design inconsistencies and generating refined CAD-files, *Optimate* aims to facilitate a streamlined workflow to enhance the efficiency in the sheet-metal design process.

3. Research methodology and objectives

While AI systems are already successfully used in various areas, this study aims to explore the effects and influence of AI supported work on the development process of sheet-metal components by applying tools as *Optimate* in the Live-Lab GSD. To operationalize the research aim, the following research questions are defined:

RQ 1: What criteria can be identified to examine the added value of AI-supported work on results of product development?

RQ 2: What influence does AI-supported work have on the development results in the Live-Lab GSD?

As part of GSD, the task of the participants is to develop a new generation of a top heat grill based on an existing reference product. For this purpose, the participants are divided into two groups of four members each. An experimental structure is introduced to investigate the influence of AI on the participating students' development results. The test group is allowed to use all available AI tools from the beginning, while the control group is only allowed to use them from the second review (end of iteration 2, cf. Figure 1) onwards. During the duration of the Live-Lab, the study participants document their use of AI and present the current state of development in fixed reviews after each iteration. To gather data, two distinct questionnaires are distributed to experts and participants, capturing both design data and participants' subjective evaluations. The influence of AI support is rated on a six-point Likert scale, from one (poor) to six (very good), allowing quantitative assessment of the received responses. In addition, open-ended questions are included to obtain general subjective impressions. In the expert questionnaire, free-text fields are provided to facilitate a deeper understanding and to help identify underlying causes of any observed deviations between the results obtained of the surveys. The questionnaires for experts and students are developed based on evaluation criteria derived from literature research.

To address Research Question 1, a literature review is conducted to identify and derive criteria suitable for assessing the added value of AI-supported work in product development. The literature review focusses on AI applications in engineering and product development, involving metrics relevant to performance, efficiency, design quality, and innovation. The selected criteria were refined and applied to assess the support AI tools on sheet-metal design within the Live-Lab GSD environment. Research Question 2 is answered by evaluating the applied questionnaires including the evaluation of the sheet metal designs of the developed grill generations of both teams.

4. Identified criteria to examine the value of AI-supported work

Samid examines the concept of AI-assisted innovation as a technology aimed at enhancing innovation productivity by supporting human creativity and efficiently evaluating innovative ideas. The approach involves a model that uses innovation history as a reference, helping innovators make decisions based on historical insights about cost, duration, and potential merit. Used techniques allow an AI assistant to interact dynamically with innovators, fostering accelerated and guided innovation pathways [13]. Further, Martinsuo and Poskela investigate the impact on innovation performance at the front end of product development. The study, based on industrial companies, finds that the use of evaluation criteria in the front end of innovation significantly promotes competitive and business potential, with informal assessment systems mediating the link between product complexity and strategic opportunity [16].

Wang, Liu, Liu, and Tao reviews AI's role in supporting various stages of Product Lifecycle Management (PLM) within smart manufacturing. AI applications in PLM span product design, manufacturing, and service, providing tools for automating tasks, analyzing data, and making predictive assessments. The study discusses how AI can enhance efficiency and innovation across PLM stages and presents a roadmap to guide future research and applications. This roadmap emphasizes opportunities and challenges, highlighting AI's potential to improve decision-making, reduce resource consumption, and optimize product lifecycle processes within the Industry 4.0 framework [14]. Automating tasks in the development process as well as supporting the innovation process itself can minimize the duration of product development processes and enhance efficiency. Therefore, the

Speed of Development is defined as one criterion to assess the influence of AI-supported work in this study. Hart et al. examine criteria companies use to evaluate new product development projects at different stages. Through analysis of 166 managers' responses, the study finds that criteria such as technical feasibility, market potential, and intuition are prioritized in the early stages, while product performance, quality, and budget compliance are crucial in later stages. In the commercialization phase, customer acceptance, satisfaction, and sales performance become primary focus areas [17]. Selecting the optimal ideas and concepts considering technical feasibility, and fulfilment of technical functionalities under budget constraints is crucial. Despite available possibilities and competencies within organizations, new product generation of technical systems must adhere to reasonable financial limitations and consider acceptable market prices. Therefore, ***Cost Efficiency*** is defined as the second criterion in this study.

Zirger and Maidique investigate critical factors that differentiate successful from unsuccessful product development efforts. The study, based on over 330 new products in the electronics industry, empirically tests a model identifying key organizational elements, development activities, and communication channels impacting outcomes. Success factors identified include R&D quality, product technical performance, customer value, product synergy with the company's core competencies, and management support during development and launch [18]. Salehi and Burgueño examine AI's role as an alternative to classical modelling techniques in structural engineering. The study highlights AI's efficiency in addressing uncertainties, optimizing design parameters, and improving computational efficiency, especially in cases where physical testing is impractical. The review categorizes recent advancements in machine learning, pattern recognition, and deep learning, noting that these AI methods are increasingly integral in tasks like structural design, decision-making, and risk analysis [12]. Utilizing AI tools in the design phase, exemplary by reducing errors, can lead to a more functional product. Reflecting technical performance and quality in research and development, ***Quality and Functionality*** is defined as the third criterion in this study.

Edilia and Larasati explore the transformative role of AI in business development strategies, focusing on AI's potential to enhance competitiveness and operational efficiency. Using a qualitative literature review, the study analyzes how AI-driven data analytics facilitates personalized customer experiences and improves decision-making processes. The study emphasizes a symbiotic relationship between AI capabilities and human judgment, suggesting that AI can function as a strategic partner that augments human expertise. This integration enables organizations to create dynamic strategies that respond to evolving demands and drive innovation in technology [11]. La Torre et al. introduces a model for optimizing team formation in settings where human and AI collaboration is critical. The authors propose a multicriteria goal programming model that considers factors like human-AI trust, technology acceptance, and self-efficacy to form teams that are more receptive to AI integration. The model's index helps allocate individuals to teams in a way that minimizes resistance to AI-enabled decision-making and supports organizational adaptation to AI-driven transformations [19]. For development projects to succeed, factors such as team leadership, goal clarity, and group cohesion are essential. Therefore, AI tools should be designed to support development activities effectively, prioritizing the development objectives. AI can improve these aspects by supporting team diagnosis and promoting the acceptance of AI-supported decisions, which leads to more efficient teamwork and higher developer satisfaction. Therefore, ***Developer Satisfaction*** is defined to assess the influence of AI-supported work in this study.

5. Influences of AI on development results

5.1. Influence of AI support on the speed of development

To assess the development speed of both groups in the conducted Live-Lab GSD, the quantity of optimized components per group is evaluated across the three iterations and is illustrated in the following Figure 2.

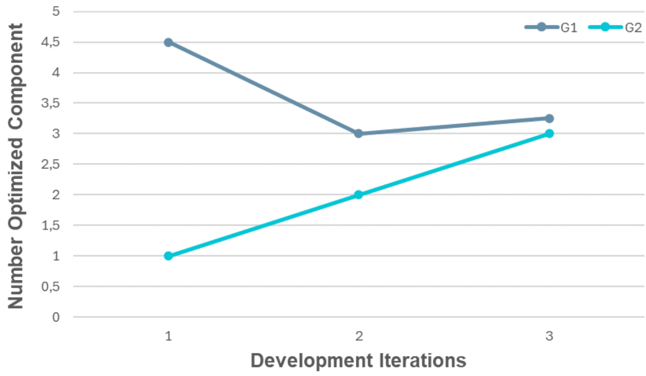

Figure 2. Number of optimized components across the development iterations for Group 1 (with AI) and Group 2 (without AI in Iteration 1)

In the first iteration, Group 1, with access to AI support through *Optimate*, achieved optimization on four components and partial modification on a fifth, while Group 2, operating without AI tools, optimized only one component. The AI tool *Optimate* facilitated Group 1's progress by providing built-in validation and optimization capabilities, enhancing efficiency in development tasks. The increase in efficiency is primarily contributed by the validation and reduction of design errors during the iteration. In the second and third iteration, Group 2 was given access to *Optimate*, which led to a progressive increase in their optimized component count. Evaluating all iterations, Group 1 achieved to optimize a total of ten components, whereas Group 2 achieved optimization on six. These results indicate that early AI support offers an advantage in development activities. Therefore, Group 1, with initial AI access, was able to design approx. five times as many optimized components as Group 2 within the same time period during the first iteration. This suggests that AI support at the early stages of development can accelerate the speed of development activities. Although Group 2 received access to *Optimate* starting in the second iteration, the total number of optimized components cannot be attributed solely to AI support. Team dynamics also played a subjectively perceived important role. Group 1, which showed stronger subjective team cohesion, likely benefited from these dynamics, contributing to their overall higher speed of development and number of optimized components compared to Group 2.

5.2. Influence of AI support on cost efficiency

To assess the cost efficiency of both groups, the estimated costs for the resulting new grill generation for each group is illustrated in Figure 3.

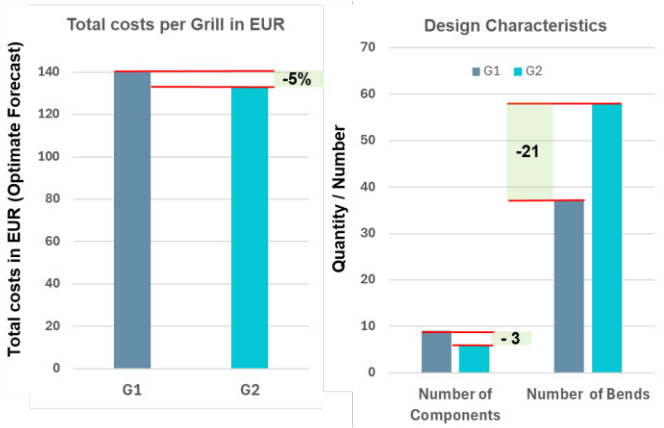

Figure 3. Comparison of the final products at the third review: (left) Cost forecast based on Optimate (10 units), (right) Design Characteristics: quantity of components and bends in the structure

Notable differences can be observed in the design characteristics between both groups. The evaluation of design characteristics and cost forecasts shows that Group 1 applied functional integration at the product level more effectively than Group 2. By merging the functionalities of multiple components, Group 1 achieved similar functionality and cost with fewer than half the components. Conversely, Group 2's higher number of bends and lower component count indicate more complex individual components. This complexity led to increased costs and unutilized optimization potential, despite available advantages of AI-assisted design in identifying and mitigating such inefficiencies. The findings suggest that early and effective use of AI-enabled functional integration can streamline design and reduce costs. Group 1 minimized component count and cost more effectively than Group 2, demonstrating how AI support can enhance cost efficiency in product development.

5.3. Influence of AI support on quality and functionality

To assess quality and functionality, the perceived degree of innovation was evaluated based on the questionnaire ratings. These ratings are collected from experts with multiple years of experience in sheet-metal design, as well as from power users and customers familiar with previous grill generations. This subjective evaluation provides insights into the innovation level of the design as perceived by users. The evaluation of the perceived degree of innovation in the grill design of Group 1 showed no major change across the initial two iterations but is rated moderately high (cf. Figure 4). However, innovation perception increased following the introduction of a modular design and additional components, which allowed for expanded functionalities. In contrast, the design approach of Group 2 remained closely aligned with the previous grill generation, focusing on incremental refinements without integrating new functionalities. As a result, due to limited divergence from the reference system, experts rated the innovation level of Group 2's design as minimal. In conclusion, these findings suggest that AI support in Group 1 facilitated a more innovative design by enabling modularity and new functionalities, while Group 2's limited use of AI resulted in only incremental improvements, underscoring the advantage of early AI integration for perceived innovation in product development.

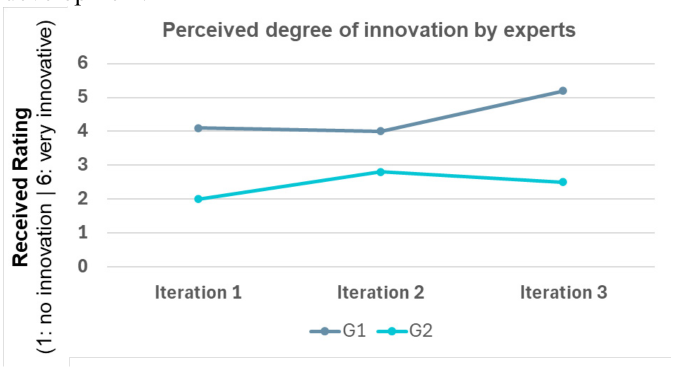

Figure 4. Degree of innovation perceived by experts from industry and customers

5.4. Influence of AI support on satisfaction of the participants

High satisfaction with results reflects the participants' positive assessment of the outcomes, indicating that the design process and final product met or exceeded their expectations. Additionally, the degree of integration of participants' own creative approaches was evaluated, capturing the extent to which individuals felt their personal ideas and solutions were incorporated into the development process. This measure of creative integration provides insight into participants' engagement and perceived influence on the final design, both of which are critical to overall satisfaction and perceived innovation within the project. Figure 5 illustrates the self-assessed satisfaction with the results obtained by the participants.

Figure 5. Participants' self-assessment of satisfaction with the results

Both groups reported high and increasing satisfaction with results throughout the project. Initially, Group 1 showed slightly higher satisfaction, reaching peak levels by the second review, while Group 2 matched these levels in the third review. This difference may stem from unassisted development in the first iteration of Group 2, possibly decelerating progress in the beginning. While AI tools like *Optimate* may enhance satisfaction, this study did not provide strong evidence of a substantial impact.

6. Summary, discussion and outlook

This research aims to examine the influence of AI-supported work on the product development process and outcomes, utilizing tools focusing on sheet-metal design such as *Optimate*. For this research the Live-Lab GSD - Generational Sheet-Metal Development is utilized as a suitable research environment. Initially, literature-based criteria for evaluating the influence of AI support in product development are identified and adapted to assess AI's influence on the four key areas: *Development Speed*, *Cost Efficiency*, *Functionality and Quality*, and developer *Satisfaction*. To evaluate AI supported work in the development process, a Live-Lab study within the Generational Sheet-Metal Development (GSD) project was conducted, providing the foundational data for subsequent analysis. The results show that AI tools enabled the test group to adopt a more complex, modular design approach, with a higher proportion of new designs and fewer component carryovers. This was further supported by the test groups higher degree of innovation, suggesting that AI contributed to an accelerated development process, given that both groups operated within the same project timeframe. For cost efficiency, the test group basic product version—chosen for its high comparability with the control groups model—was evaluated. Results indicated that both products achieved a similar price level. The higher number of components in the test group was offset by the increased number of bends in the control group, balancing the overall cost. The test group, however, exhibited greater cost optimization potential, indicating that AI tools such as *Optimate* helped achieve more cost-effective designs. In terms of quality and functionality, the test group's design showed fewer errors and a more functional modular design, achieving comparable quality with enhanced functionality. Regarding the influence on perceived satisfaction, no major influence could be verified. Although the test group showed an increased contribution of their own creative ideas, this did not positively affect the participants' satisfaction. Despite an observed positive influence on satisfaction and facilitating creative input, a clear connection to AI tools cannot be proven. Several limitations are noted, including the small sample size (four experts and four students), which restricts the study's generalizability. Future studies will address this by increasing the sample size, extending the observation period, and conducting additional reviews to capture adaptation to AI tools more thoroughly. Repeating the Live-Lab with more participants would also allow for statistical validation of AI's positive effects on product development outcomes. This exploratory study suggests that AI can positively influence development outcomes in Live-Labs, with further studies needed to substantiate these findings.

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