XDP-Opt: Experience-Based Design Process Optimization for Industrial Manufacturing

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Abstract
A comprehensive approach to product development involves evaluating all aspects of a product's lifecycle, from the initial design phase to its end-of-life. Design for Excellence assessment software integrated into a Computer-Aided Design (CAD) environment helps to identify potential issues early, and ultimately avoid costly mistakes during the development of new products. However, this software is predominantly bound to strict rule-based reasoning, which does not account for subtle design constraints and provides no solutions to detected problems. The research project XDP-Opt addresses these problems by developing an Interactive Design Decision Support System. It utilizes a combination of federated foundation models and Case-Based Reasoning to discover problematic design features and suggest solutions for these based on historical CAD data. This paper gives a literature overview on the problem the project is concerned with and shows the core concept and the components of the AI core of the proposed support system.

Keywords
Case-Based Reasoning, Design Decision Support, Federated Learning, Foundation Models, Design for Manufacturability

1. Introduction

Global megatrends are reshaping manufacturing and, consequently, the process of designing and engineering new products, commonly referred to as New Product Development (NPD). These trends encompass societal, environmental, technological, and political challenges [1]. Since NPD is a highly experience-driven activity, companies are particularly vulnerable to knowledge loss within the workforce. Therefore, demographic change, especially in developed regions, poses a major challenge for manufacturing businesses [2]. Product designers must take the entire product lifecycle into account, relying on expertise in production capabilities, customer needs, and prior designs. Strong design skills are typically acquired through years of experience. To prevent knowledge drain, companies must capture, model, and transfer this expertise to future designers, either through structured training or real-time support systems [3]. The sustainability transformation is further disrupting NPD by altering product requirements, production processes, and resource usage. At the same time, rapid technological developments demand shorter improvement and validation cycles. As a result, product designers must be supported in optimizing their design and engineering workflows.

Design for Excellence (DfX) assessments integrated into development environments can specifically support inexperienced product designers by helping them identify design flaws early and accelerate design iterations [4]. Current DfX software primarily relies on rule-based validation methods. While these rules are effective at identifying certain design constraints, they often fall short in capturing more nuanced limitations or complex factors arising from real-world manufacturing and assembly

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processes. Moreover, such tools typically lack the capability to suggest viable design modifications, leaving engineers to address issues manually, even in cases where existing solutions could be adapted.

This paper introduces the research project Experience-Based Design Process Optimization for Industrial Manufacturing (XDP-Opt), which addresses the aforementioned challenges by developing an Interactive Design Decision Support System (IDDSS) to support product designers in adhering to Design for Manufacturing (DfM) principles. The system validates designs within the Computer-Aided Design (CAD) environment using learned manufacturability assessments and suggests mitigation strategies for problematic design features by identifying similarities to previously resolved design issues. These are inferred from historical CAD data. The paper outlines the project's starting point based on existing literature and presents the conceptual foundation of the IDDSS, with a focus on its core logic. It also discusses the technological foundations necessary for the implementation of such a system. The guiding research question is: How can a conceptual framework for an interactive design decision support system be developed to enhance manufacturability validation and facilitate knowledge reuse in CAD-based product development processes? This work introduces the system's design, considers its potential benefits, and sets out its underlying principles, while postponing detailed empirical evaluation and methodological studies to future work.

The structure of the paper is as follows: Section 2 reviews foundations for the projects initial point; Section 3 presents the conceptual design of the IDDSS; Section 4 examines the suitability of federated foundation models and Case-Based Reasoning (CBR) as the system's core technologies; Section 5 discusses potential impact and validation approaches; and Section 6 concludes the paper.

2. Foundations

In contrast to traditional knowledge-driven rule-based frameworks, the integration of data-driven Artificial Intelligence (AI) and machine learning into product design and manufacturability assessment offers greater flexibility and adaptability. Accordingly, this section reviews not only the current state of DfX and manufacturability validation (Section 2.1), but also explores the application of foundation models in product design reasoning (Section 2.2) and AI-driven decision support in product development (Section 2.3). Finally, Section 2.4 highlights unresolved challenges and identifies opportunities for future research.

2.1. Design for Excellence and Manufacturability Validation

DfX is an integrated approach for NPD that emphasizes the consideration the impact of design decisions in all following product lifecycle phases [5]. The goal is to drive an integrated design approach in which design adaptations are conducted as early as possible during the development phase of the product lifecycle. This is motivated by the steadily increasing cost of changes during NPD [6]. Popular dimensions of DfX are manufacturability, assembly, inspection, disassembly, cost and many more [5].

DfM focuses on ensuring that a product can be manufactured efficiently and economically, while maintaining quality standards. Traditional DfM methods rely on rule-based design guidelines that help engineers assess manufacturability constraints early in the design phase [7]. Predictive manufacturability assessment is the flip side of DfM by simulating and evaluating the product design's manufacturability based on predefined heuristics or process-specific constraints. These methods have been widely adopted in industries such as aerospace, automotive, and consumer electronics [4].

More and more recent work also includes the utilization of machine learning as surrogate models for extensive process simulations to estimate manufacturability [8]. These models offer the capability to substitute time- and cost-intensive simulations whenever a deterministic and precise solution is not required. Also, they can infer subtle manufacturability constraints from historical data wherever they cannot simply be formulated as rules [4].

2.2. Foundation Models for Product Design Data

Foundation models have revolutionized various domains, like marketing, software development or customer service, by enabling deep learning systems to generalize across diverse tasks [9]. While their success is well documented in natural language processing and computer vision, their application to product design data remains an emerging field [10]. This encompasses CAD models, tolerances, material properties, and manufacturing constraints.

The authors in [11] performed an exploratory analysis of the potential applications of foundation models in CAD workflows by focusing on purely unimodal text-based and outputs. They identified potential for the generation of CAD files from text, design space exploration in variant generation, assessing manufacturability options, manufacturability design validation and correction, generating instructions for manual assembly as well as machine code and multi-objective design evaluation.

Some of these have already been explored in other works [12, 13, 14]. Other publications also explored the capabilities of foundation models in natural language processing for querying and question answering on CAD models [10, 15] or model autocompletion [16].

The authors in [11] also identified several risks that come with the use of these models for CAD workflows, such as job displacements, intellectual property conflicts, reliability and accountability issues, data privacy and more.

2.3. AI in Supporting Design Decisions in Product Design

AI has emerged as a transformative tool in product design, particularly in supporting decision-making throughout the design process. By leveraging advanced computational techniques, AI enhances various stages of product development—improving efficiency, fostering creativity, and promoting sustainability. A growing body of research has investigated the integration of AI into product design and development. AI-driven approaches have been successfully applied in areas such as generative design [17] and recycling-oriented product development [18], leading to more effective and innovative design outcomes. The literature highlights several methodologies, including multi-agent systems [19], model-based design [20], and probabilistic inference [21], as means to support and optimize design processes. Furthermore, applications of big data analytics [22], design automation [23], and intelligent tutoring systems [24] have been explored in both product development and design education contexts.

A particularly relevant AI approach for supporting design decisions is the use of Decision Support Systems (DSS). Ming et al. underscore the increasing significance of AI-based DSSs in contemporary product design, highlighting their potential to tackle complex challenges, foster innovation, and enhance decision-making efficiency [25]. Research in this domain focuses on developing DSSs that aid designers in making informed decisions and generating creative solutions. Commonly employed techniques include clustering [26], neural networks [26], fuzzy set theory [27], and dynamic programming [28].

Despite notable advancements, current approaches to AI-based decision support systems often overlook the integration of experiential knowledge, which refers to insights gained from practical, hands-on experience. This omission is particularly evident in the early stages of design, where decisions are typically intuitive and highly context-dependent. In both academic research and tool development, predominant strategies emphasize formal methods, abstract models, and data-intensive techniques. However, these approaches are seldom adopted in industrial practice due to their limited applicability, high data demands, and misalignment with the way designers typically work, as they rely heavily on experience, intuition, and tacit knowledge [29]. CBR has been proposed as a promising approach to address this gap, referring to a problem-solving paradigm that reuses past cases or experiences to find solutions for new problems [30]. In product and architectural design, CBR leverages prior cases to support decision-making in new, context-specific situations. For example, in architecture, CBR has been successfully applied to tackle novel design problems based on experiential knowledge, and these methods can be adapted to product design [31]. Other studies explore how CBR can be applied in structural design by conceptualizing the process as the recall and adaptation of past design cases to meet constraints in new contexts [32]. In the field of new product development, research has investigated how past experience can enable and support decision-making in the early stages. In this context, a case represents a product development situation, including contextual factors, decisions made, and outcomes. Past cases serve as a knowledge base, allowing designers to address similar challenges more efficiently. These cases are typically represented in an attribute-based structure with key-value pairs, which facilitates systematic retrieval and adaptation [29].

2.4. Research Gaps

Although recent years have seen significant progress in supporting product designers, several issues remain unresolved. For instance, the use of foundation models in design verification has so far received insufficient attention in research. DFM assessments are often limited to the data available within individual companies, highlighting the need for mechanisms to share experience and thus enable more generalized assessments. Moreover, recent findings indicate that experience-based support systems are more suitable for real-world design environments. A major challenge in developing experience-based decision support systems is the representation and structuring of DfM knowledge in a reusable case base, which is essential for effective experience transfer. Closely related is the retrieval of relevant design cases within CAD environments, including technical drawings, where efficient mechanisms for searching complex geometries and design features are still underdeveloped. Another critical issue is the cold start problem, as many systems require extensive historical data to provide meaningful recommendations and currently lack strategies to operate effectively under data-sparse conditions. In addition, IDDSS must provide explainable recommendations that allow product designers to understand and trust the reasoning behind the system's suggestions. Despite these needs, practical frameworks for systematically capturing and utilizing experiential knowledge within organizations remain limited [29].

3. XDP-Opt Concept and Architecture

The challenges, outlined in Chapter 2.4, are addressed by the research project XDP-Opt, which proposes a support system for NPD. It is based on an iterative design loop, as depicted in Fig.1, which is derived from the V-model for system development [33]. It also aligns with the workflow of established engineering change management practices, as commonly implemented in product lifecycle management systems [34].

The primary goal in XDP-Opt is to strengthen the early stages of the product development process within existing industrial manufacturing environments through a hybrid IDDSS. This support system consists of two components. A Design Validation Model reviews the current state of the design project and detects problematic design decisions, which represent violations of best practices. A Design Recommendation System then suggests solutions to these problems.

The IDDSS integrates experiential knowledge from product designers and historical data from the iterative design loop. While the product designer, as the primary user, interacts with the CAD environment, the IDDSS imports the current state of a design project (consisting of CAD models, technical drawings, material allocations, etc.) from the CAD system. Firstly, these artifacts from the design process are assessed by the Design Validation Model, that represents design constraints. If violations against these constraints are detected, this component generates problem descriptions that are submitted in the form of standardized Problem Report (PR)s to a product lifecycle management system. These describe the violation itself, its reference location on the part, and rate the severity of the violation.

The Design Recommendation System imports these PRs and suggests possible solutions to the user. These solutions are based on solutions to similar problems from the past, and hereby leverage expert knowledge and experience. The Design Recommendation System exports the solutions in the form of standardized Engineering Change Request (ECR)s linked to the corresponding PRs. An ECR contains mainly a description of a proposed solution to its related PR specifically adapted to the concerned part. The ECRs are then implemented by the user in the CAD system. Important to note here is that the

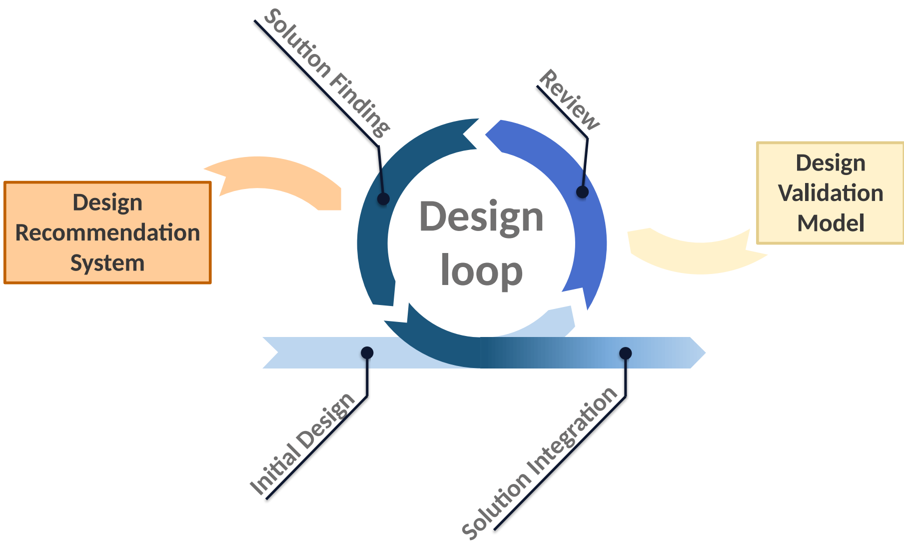

Figure 1: Iterative design cycle and the design phases that will be supported by the system.

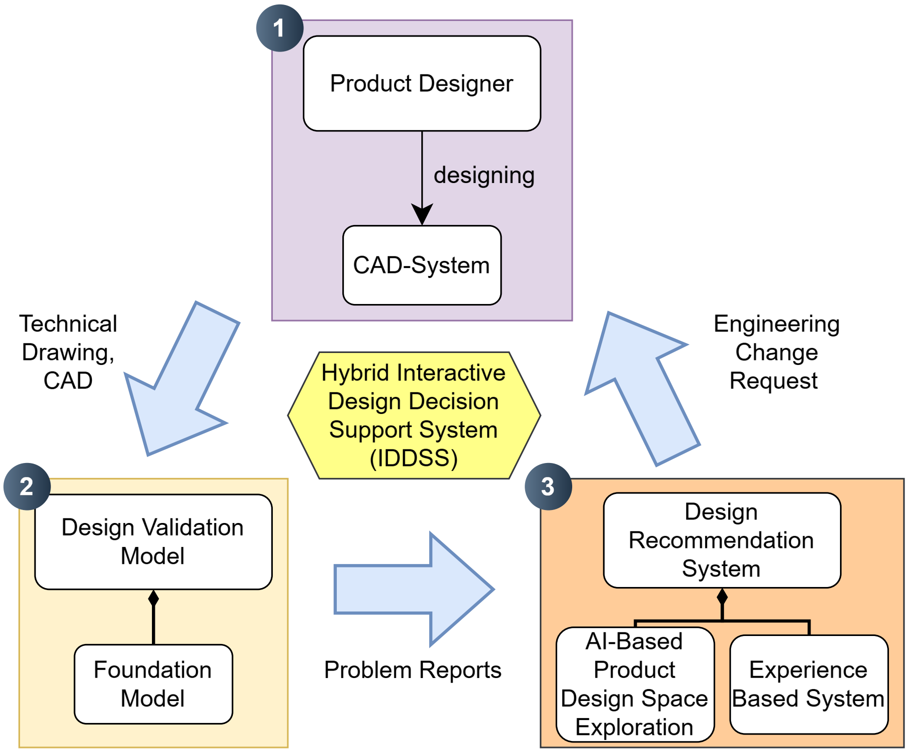

Figure 2: Components and processing sequence within the XDP-Opt concept. The process represents the sequence in engineering change management [34].

system makes the PRs and ECRs as suggestions, and the user needs to accept or decline the generated suggestions. Fig. 2 shows the total sequence and the components as parts of the IDDSS. The whole validation and change process sequence can be triggered by the user at so-called decision points. These represent either freely chosen points triggered by the user during the creative design phase (e.g., for reassurance, inspiration, etc.) or mandatory points during the NPD process (e.g., in a phase-gate process). The components are explained in more detail in the following.

Product Designer: The product designer specifies a drafted product architecture into an initial design, which is verified in the following to ensure manufacturability among other requirements. Problematic or suboptimal design decisions and features are identified, and individual solutions are defined and incorporated into the product design. This initiates the design review phase in the next iteration. Fig. 1 illustrates the proposed system. It would support this iterative design approach during the review phase to detect suboptimal design decisions and the solution finding phase to adapt successful solutions from experience.

Design Validation Model: The task of the Design Validation Model is to identify issues with the adherence to best practices by processing the current state of the design project. These best practices are often times soft constrains to design that represent preferences of the company, for example regarding preferred tools. Thus, the model must be flexibly adaptable to new individual preferences and also notice subtle problems arising from the interaction of different problematic decisions.

Design Recommendation System: The recommender system consists of two main modules: the AI-based Product Design Space Exploration (AI-PDSE) and the Experience-Based System. The Experience-Based System module processes PR and proposes multiple solution options in the form of ECR, based on solutions to similar issues encountered in the past, while also leveraging associated information such as CAD files, technical drawings, and product requirements. Users can either accept or reject these proposals, and their feedback is used to refine and improve future recommendations. To address the cold start problem, when no prior knowledge about solutions is available, the AI-PDSE module is used. It derives the product design space from the domain model and generates new potential solutions for the identified problems. This component dynamically adapts to the design environment, offering possible actions and recommendations. It highlights the implications of design decisions and suggests innovative options beyond those found in historical experience.

4. Suitable Core Technologies

The implementation of the XDP-Opt architecture requires the use of advanced AI technologies tailored to the needs of design validation and recommendation. Given the complexity of modern design processes and the sensitive nature of industrial design data, it is essential to apply methods that support multimodal data processing, knowledge reuse, and privacy-preserving collaboration. To address these challenges, the system incorporates three key technological approaches: foundation models, Federated Learning (FL), and CBR. Each of these technologies contributes in a specific way to the functionality and performance of XDP-Opt. This section introduces these selected technologies, outlining their roles within the system and discussing their respective strengths, limitations, and relevance in the context of NPD.

4.1. Design Validation Model

For the realization of the concept, a suitable logic must be found to power the individual components. Similar to comparable related works, we decided to use a foundation model for the Design Validation Model. It offers the necessary flexibility and multimodal processing capabilities to ingest a complex design project. Fine-tuning it to the specialist task of DfM validation on CAD data, promises to be a highly data-intensive task. However, the availability of this data, is one of the main drawbacks of this approach, as product-related CAD data and manufacturing know-how belong to the most sensitive intellectual property for a manufacturing company. One privacy-preserving way to utilize a larger amount of data is FL.

Unlike centralized methods, FL allows multiple clients, such as mobile devices or organizations, to collaborate in model training without sharing raw data [35]. Instead, model parameters or gradients are shared during between the clients, who independently train on their own subset of the total data.

The increasing interest in FL for applications in fields such as healthcare, finance, and IoT, where data privacy is crucial, [35] shows that it is a considerable solution for the Design Validation Model. Hegiste et al. even discuss FL for very sensitive data from industrial optical product quality inspection in manufacturing [36].

In the case of XDP-Opt, the utilized data consists on the one hand of artifacts from the design process, such as the product geometry, material information or other dimensioning information. On the other

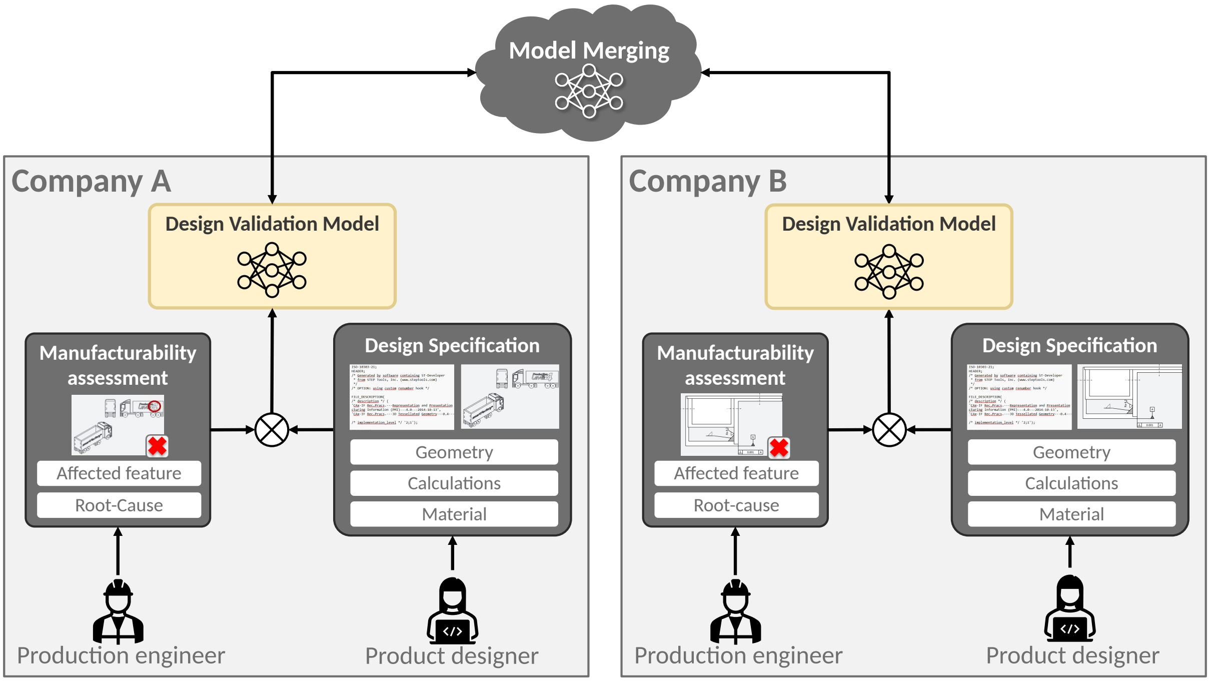

Figure 3: Training the DfM expert model in a cross-silo FL setup.

hand, manufacturing experts deliver problem descriptions, that have been traced back to problematic design specifications. This information is concatenated on the company level (in e.g. product lifecycle management systems) and used to fine-tune a Design Validation Model locally. These local models can be merged with other models to a global model with better generalization capabilities. This global model is then again distributed among all participants of this FL network. Fig. 3 illustrates the utilization of FL for the Design Validation Model and shows the affected data.

In the scope of the project, the data is sourced from the product development (variants of a model truck) at the industrial testbed of SmartFactory^{KL} and generated at scale in experiments involving students of the mechanical engineering department of the University of Kaiserslautern-Landau (RPTU). The focus lies primarily here on 2D CAD data as it carries all information necessary for production and is the usual form of technical documentation submitted by product designers to manufacturing. Thus, the project attempts to fine-tune a Vision Language Model for the task of analyzing these 2D technical drawings. The so sourced data will suffice for a proof-of-concept of the local-finetuning. It can be artificially split into different clients to validate the up-scaling correlation of the model performance and the utilization of complementary data using FL. The implementation of the federated model fine-tuning will be conducted using the FL-framework Flower [37].

Nonetheless, applications in FL face several challenges, such as communication overhead [38] and heterogeneity [39]. Notably, the model updates might still carry recoverable information about the original training data [40].

4.2. Design Recommendation System

One promising approach to leveraging experiential knowledge in recommender systems is CBR, as already mentioned in the previous chapter. Such systems support design decisions by reusing knowledge stored in structured cases, making them particularly suitable to bridge the gap between formal AI methods and the intuitive practices of designers. At their core lies a repository of previous cases whose solutions are adapted to address new problems [30]. This paradigm encompasses both system development and a wide range of practical applications, underscoring its versatility and cross-domain relevance [41]. The reasoning process, as described by Aamodt and Plaza [42], follows four main steps: retrieve, reuse, revise, and retain. The system first identifies the most relevant past cases based on a similarity metric, applies their solutions to the current problem, modifies them if necessary, and finally stores the validated solution for future use. Unlike traditional rule-based systems, this approach addresses problems by referencing specific past experiences rather than relying on a comprehensive set of formal rules. This makes it particularly well-suited for domains without clear computational or mathematical models. In NPD, where design decisions are often complex, uncertain, and poorly structured, experiential reasoning provides a practical alternative to classic knowledge-based methods [29]. Systems based on this principle have been applied in numerous fields, including help desks, customer service, e-commerce recommender systems, medical diagnosis, image processing, law, technical troubleshooting, design, planning, computer games, and music [30]. However, few studies have addressed the reuse of design and management decision-making experience in the context of NPD [29], and although literature exists on the application of CBR in product design, the focus has not been on Design for Manufacturing (DfM) knowledge. In particular, there is a need for retrieval of CAD models and technical drawings without the necessity of extensive prior classification. Nevertheless, the context of industrial manufacturing imposes unique requirements. Early design stages frequently lack sufficient historical knowledge, making a purely experience-driven approach insufficient. To overcome this limitation, the XDP-Opt framework integrates an AI-based Product Design Space Exploration (AI-PDSE) module capable of generating novel design solutions beyond the existing case base. Potential techniques for this include AI planning [43], constraint-based reasoning [44], and generative AI [45]. In complex and uncertain domains where tacit knowledge and subjective reasoning are central, the usability of AI-driven tools depends not only on the quality of their solutions but also on the transparency of their reasoning. A key advantage of experiential reasoning lies in its analogy-based nature, which enables clear explanations of how solutions are derived. This transparency makes the approach particularly suitable for supporting explainable AI in design contexts, where trust and comprehensibility are essential. The XDP-Opt project aims to build on this strength by embedding analogy-driven reasoning into its framework to provide interpretable, user-centered decision support. Unlike many high-performing AI systems that operate as opaque black boxes [46], this approach inherently clarifies which features influenced similarity assessments, why particular solutions were retrieved, and how prior experience informs new recommendations. Unlike traditional applications of CBR in domains such as architecture, where cases often consist of static geometric designs or architectural patterns, the adaptation of CBR in XDP-Opt addresses the dynamic and highly iterative nature of CAD-based product development in industrial manufacturing. The cases in our approach integrate multimodal data—including parametric CAD models, material properties, and manufacturability constraints—rather than purely visual or textual information.

5. Discussion

The concept describes a novel approach to DfM analysis that is integrable into modern CAD-based design workflows. The proposed IDDSS possesses several advantages over traditional rule-based DfM systems. Firstly, the system can adapt to complex design constraints and historical manufacturing data, allowing more nuanced manufacturability assessments. There the need for more flexibility is already underscored in [4]. This also enables the IDDSS to be flexible enough to incorporate other DfX aspects, from later lifecycle stages, like disassembly, remanufacturing or inspection in accordance to [5]. In extension to this, the use of FL allows for cross-company utilization of manufacturability data while preserving data privacy, which could lead to a more generalized and robust assessment model. The integration of CBR enables the reuse of past design solutions, therefore capturing the knowledge and learnings from past mistakes. Thus, the approach can contribute to reducing the design iteration time and improving decision-making.

Nonetheless, the concept also bears a few challenges with it. High-quality, diverse datasets, need to be collected to fine-tune a foundation model and feeding the CBR system. This requires feature-based design data formats that concentrate the essential information into a compact form. It also requires the creation of a new information model to capture the solution of design problems during iteration. This may pose a challenge when filling the case base for the CBR system. It needs to be engaging for the user to give a good description of a new case after solving a problem, so the case base is steadily growing. Furthermore, to enable an effective and efficient retrieval of relevant design cases, advanced semantic similarity methods must be implemented. In addition, the AI-PDSE component must be able to propose novel product design solutions that go beyond retrieval. Using generative models conditioned on the design constraints and goals specified by the user, the system can suggest alternative solutions that comply with technical, regulatory, and user-defined requirements. This requires a tight integration of knowledge representation. In addition, data from production and NPD are among the most sensitive types of data in a manufacturing company. As a result, companies might be hesitant to share even the model weights during federated learning. Thus, risks of data leakage through model inversion must be precisely characterized and weighted against the potential gains of a collaboration.

6. Conclusion

This paper introduced the core concept of the XDP-Opt project, which addresses manufacturability validation challenges in CAD-based NPD through an IDDSS. The proposed system integrates a fine-tuned foundation model to detect design flaws, a CBR system for adaptive solution recommendations with understandable explanations of how decisions are made, and a FL approach for collaborative model training while preserving data privacy. To validate the concept, a prototype will be tested in the industrial truck manufacturing test environment at SmartFactory^{KL}. The project aims to advance foundation models for product design data, explore cross-company collaboration via FL, and evaluate CBR's ability to adapt past solutions to new design challenges. XDP-Opt aims to demonstrate the potential of data-driven and experience-based DfM over traditional rule-based approaches.

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Declaration on Generative AI

During the preparation of this work, the authors used GPT-4o in order to: Grammar and spelling check, and simple reformulations. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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