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iAssist – Explainable AI-Based Eco-Design Support

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Abstract

Engineers determine around 80 % of a product's future costs and emissions during the design phase, such as material efficiency, production waste, manufacturing effort and assembly. The problem is that existing support in design engineering lacks systematic integration of quantifiable sustainability metrics into the design of sheet metal products. This research addresses the gap by evaluating iAssist, an explainable AI-based eco-design support that integrates sustainability metrics directly into the design of sheet metal products, such as material thickness, laser cutting waste, weld seams and part count. iAssist combines CAD-based model analysis, automated detection of eco-design optimization potential, and tailored feedback using a structured design knowledge base. It thereby enables real-time, explainable design support. In three empirical studies involving 510 sheet metal designs, the rate of eco-design alternatives increased from 5% without support to 51% with the use of iAssist. Results indicate that combining predictive assessment with real-time, explainable feedback enables engineers to make more informed and sustainable design decisions. iAssist contributes a scalable approach for embedding sustainability into early-phase engineering workflows.

Keywords: Eco-design methodology, Explainable artificial intelligence (AI), Sheet metal

1. Introduction

The design of sustainable products is becoming an increasingly important part of engineering practice. Given the increasing regulatory pressure, changing customer expectations, and growing environmental challenges, the reduction of product-related emissions has become both a strategic and ethical necessity. Early-stage design decisions hold enormous potential for ecological innovation and emission reduction across the entire product life cycle [1–3]. However, integrating sustainability into engineering design processes remains a complex and underdeveloped task in many industrial contexts.

A significant lever lies in the early stages of product development, where decisions on materials, manufacturing processes, and geometry largely determine a product's environmental footprint. Despite this, sustainability metrics are often considered only retrospectively or are guided by tacit knowledge rather than systematic evaluation [4]. There is a lack of design methods, evaluation tools, and digital support that help design engineers proactively assess and reduce emissions during the conceptual and embodiment design phases [5–7].

Although the "Ten Golden Rules" [1] or Design for Manufacturing and Assembly (DFMA) offer foundational guidance, they often remain too generic or lack validation for complex, real-world design decisions [2,8]. Metrics for evaluating the environmental impact of design alternatives during development are rare, and practical guidance on their effective application, such as for material efficiency, production waste, manufacturing effort, and assembly, is often lacking.

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The problem is that existing support in engineering design lacks systematic integration of quantifiable sustainability metrics into the design of sheet metal products. This paper therefore aims to contribute to the evaluation of an AI-based eco-design support that combines empirical measurement, digital assistance, and contextual training to improve designers' ability to recognize, develop, and evaluate sustainable design alternatives. By building on existing findings and extending them with new methods, the proposed support seeks to establish a data-driven, reproducible and scalable foundation for sustainable design practice in the example of sheet metal design.

2. State of Research

The design phase plays a critical role in determining the environmental footprint of products, with estimates suggesting that up to 80 % of a product's future emissions and costs are set during early development stages [1–3]. Despite this significance, sustainability is still perceived in many companies as a constraint rather than a design objective [9]. A survey by [2] found that only a minority of manufacturing companies systematically consider sustainability metrics or environmental impact during design, while economic factors such as cost dominate decision-making. Similar patterns have been observed in other international studies [3], emphasizing the global nature of this challenge. These findings reveal a tension between traditional design priorities and environmental performance, highlighting the need for support in designing more sustainable products in alignment with mechanical functionality. Moreover, current sustainability strategies in industry often focus on optimizing operational efficiency, such as reducing machine run times and minimizing interruptions, rather than addressing sustainability already at the design stage [10].

Various supports have been proposed to incorporate sustainability into product design. [1] introduced the "Ten Golden Rules" as a set of general design guidelines for environmental considerations, focusing on topics such as material selection, energy efficiency, repairability, and recyclability. While these rules offer valuable principles, their abstract nature and lack of validation limit their direct applicability in industrial context, especially for engineers requiring clear, actionable support in specific manufacturing domains like sheet metal design. Furthermore, these guidelines were not developed with quantifiable sustainable metrics in mind, leaving a gap in connecting design engineering with quantifiable outcomes.

A more practice-oriented and quantifiable methodology is DFMA, which aims to reduce product complexity and improve resource efficiency by simplifying parts, interfaces, and assembly processes. [11] demonstrated that DFMA can yield substantial environmental benefits: in a case study of a redesigned sheet metal product, CO_2 emissions from production processes were reduced by 60.2 %, and total emissions, including raw material use, by nearly 29 %. These results were confirmed by [8], who affirmed DFMA's potential to lower environmental impact through design simplification. However, DFMA is not inherently focused on sustainability analysis, and its application still requires engineers to manually interpret sustainability impacts without integrated feedback systems. Recent commercial solutions, such as Siemens NX, have introduced sustainability features based on the EN15804, combining 3D design data with AI-based material recommendations. While this software offers a relevant step toward integrating sustainability into product development, the primary focus lies on environmental indicators at the material level and does not yet extend to quantifiable metrics for evaluating design alternatives. Moreover, the design alternatives in sheet metal design are central rather than material substitution, which remain insufficiently supported.

Consequently, a key limitation in the current state of research is the lack of support that allows engineers to systematically evaluate and compare the environmental impact of their design alternatives in a quantifiable way. Although DFMA promote sustainability in principle, there is a lack of data-driven, real-time feedback or seamless integration into day-to-day design processes such as [12]. The problem is that existing support in engineering design lacks systematic integration of quantifiable sustainability metrics into the design of sheet metal products. This underlines the need for design support that bridges sustainability and engineering requirements in a process-integrated and actionable manner.

The aim of this research is to investigate to what extent different levels of integrated sustainability support, ranging from no support to training content and the AI-based tool iAssist, improve design alternatives with respect to sustainability metrics in sheet metal product development. While existing design methods such as DFMA offer general sustainability guidance, they fall short in providing actionable, real-time feedback on the environmental consequences of design alternatives. To address this gap, an explainable AI-based eco-design support, iAssist, will be evaluated, supporting engineers in comparing design alternatives. However, the evaluation does not include yet mechanical functionality or manufacturing feasibility, which needs to be ensured by the design engineer during the subsequent validation process. Accordingly, the following research question is posed: *To what extent do different levels of integrated sustainability support, ranging from no support to training content and iAssist, improve the design alternatives with respect to sustainability metrics?*

3. Material and Methods

3.1. iAssist

Process of iAssist: The presented support aims to systematically integrate sustainability metrics into the design of sheet metal products through the application of AI-based analysis and continuous increase of design knowledge as shown in figure 1.

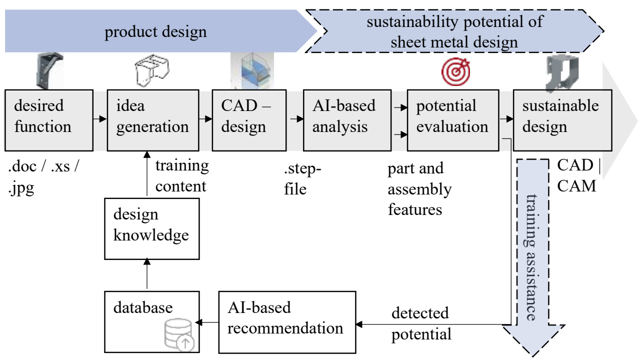

Fig. 1. Process of iAssist to systematically integrate sustainability metrics in a quantifiable and practically applicable manner.

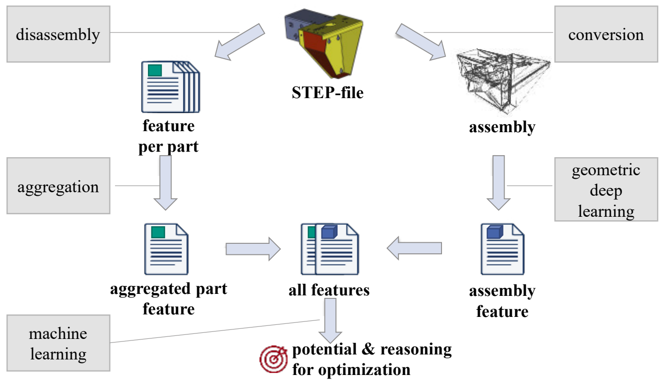

Fig. 2. Process of AI-based analysis.

The process of iAssist starts with a detailed analysis of functional requirements, encompassing cost targets, assembly constraints, part quantities, and additional performance criteria, which are documented in various digital formats (e.g., DOC, XLS, JPG). Based on these requirements, initial conceptual designs are developed by the design engineer and evaluated through a structured ideation process, ensuring alignment with both functional and sustainability objectives.

The resulting concepts are subsequently translated into detailed CAD models specifically optimized for sheet metal applications, thereby facilitating accurate automatized analysis. AI-based analysis is then applied to the CAD models, utilizing STEP files to extract relevant part and assembly features that directly influence sustainability metrics. The identified features undergo an evaluation to assess the sustainability potential of the design, enabling the identification of improvement opportunities related to for example material use, manufacturability and number of parts. To assess the sustainability of the sheet metal design, 70 metrics were defined in line with principles of material efficiency, production waste reduction, and assembly simplification. Seven out of 70 metrics are following: average material thickness and material utilization rate reflect raw material efficiency and cutting layout effectiveness. Internal production waste and laser cutting waste ratio quantify material loss during development and manufacturing. Total weld length and weld joint count serve as proxies for energy consumption and process complexity during assembly. The part count indicates overall system complexity and disassembly effort. These metrics enable a structured comparison of design alternatives and help identify trade-offs between functionality and environmental impact.

Process of AI-based analysis of CAD models: To identify optimization potential and its underlying reasoning from STEP-files, two distinct processing pathways were implemented as shown in figure 2. The first pathway involves a disassembly of the STEP-file into individual components, followed by feature extraction per part.

These features are then aggregated to form a comprehensive representation of the entire assembly. In contrast, the second pathway begins with a conversion of the STEP-file into an assembly model, which is subsequently analysed using geometric deep learning to derive assembly-level features. Both pathways culminate in a unified stage where all features, aggregated part features and assembly features, are combined. This consolidated feature set serves as input for a machine learning model, which is trained to detect optimization potential and provide reasoning for the proposed improvements.

There are two possible outcomes of the AI-based analysis: On the one hand, if no optimization potential is detected, the sheet metal design is considered optimal with respect to sustainability metrics, providing engineers with support in comparing design alternatives. However, the evaluation does not include yet mechanical functionality or manufacturing feasibility, which needs to be ensured by the design engineer during the subsequent validation process. On the other hand, if optimization potential is identified, the system performs AI-based mapping of the identified features to assigned training content, which is then stored in a continuously evolving database of product design knowledge. This design knowledge is subsequently leveraged to extend the design competencies of engineers by providing context-specific training content during the design iterations. Through its iterative and data-driven mechanism, iAssist provides process-integrated design support that integrates quantifiable sustainability metrics. In doing so, it enables engineers to evaluate and compare design alternatives based on environmental impact, thereby addressing a key gap in current design processes and contributing to improved engineering outcomes in sheet metal product development.

The combination of prediction accuracy and the simultaneous explainability of potential assessments serves as a foundation for generating targeted, user-specific training recommendations within the iAssist support.

Training content database: The e-learning design knowledge database utilized in iAssist is hierarchically structured to systematically support engineers throughout the product development process, an example can be seen in figure 3.

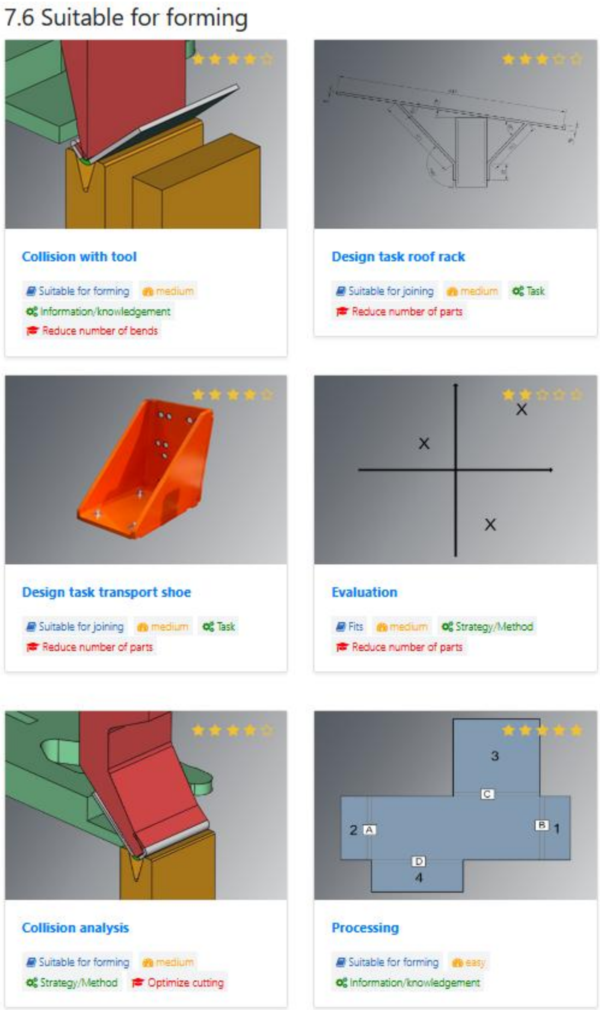

Fig. 3. Design knowledge database: example illustration 6 of 116 training contents.

The database is structured into training modules: *Introduction* module, establishing the scope and objectives of the design process. Subsequent sections on *Problem Solving Process* and *Product Development Methods* provide methodological foundations for structured and efficient problem analysis and solution generation. *Engineering Basics* deliver essential technical knowledge, which is further developed in the *Conceptual Development* modules, subdivided into *Basics*, *Functional Aspects*, and *Requirements*, to guide systematic concept creation. Dedicated modules on *Design Elements* and *Technical Elements* offer practical guidance for the detailed design and technical realization of products. Finally, an *Industry* section complements the database with applied examples and case studies, facilitating the transfer of theoretical knowledge into industrial contexts. Each of the 116 training contents has the same structure as shown in figure 3.

Each training content is uniformly structured and includes a heading, the objective of the content, metadata for AI-based analysis, a detailed description of the design method, references to related design methods, relevant sources, and recommendations for additional methods within the same category or subcategory.

AI-driven recommendation of training content:

To enable targeted training content recommendations, two complementary pathways were developed. The first pathway utilizes the AI-driven analysis of CAD models, where features derived from the product's geometry and identified optimization potential are used to recommend relevant training content. In parallel, the second pathway incorporates user preferences, gathered through onboarding questionnaires and user feedback, to tailor recommendations to individual needs for training content. Both pathways independently generate prioritized lists of training content, which are then merged into a personalized recommendation. This recommendation draws from a structured database of training modules. By aligning training content with both technical design features and user-specific learning profiles, iAssist supports the systematic enhancement of design knowledge through AI-based personalization.

3.2. Study design

The number of sheet metal designs generated across three different studies conducted in Germany and China are summarized in table 1. The first study was carried out without any support, resulting in 14 designs in Germany and 25 in China. In the second study, participants were provided with training content, leading to 37 designs in Germany and 49 in China. The third study involved the use of the explainable AI-based eco-design support iAssist, which supported the creation of a total of 385 designs across both countries. The higher number of designs generated using iAssist compared to those created with the training content and no support can be attributed to the autonomous nature of the software-based approach, which did not require direct human facilitation. This likely increased participant engagement and willingness to design alternatives, as the barrier to entry was lower. Within the study design the design engineers were allowed to freely design their own sheet metal design alternatives. The advantage of such study design is to reflect real-world conditions, where diverse designs naturally emerge. As a result, the study enabled the evaluation of a wide range of individual sheet metal designs without prescribing a specific task.

Table 1. 510 sheet metal designs in three studies.

Support type in the study	Germany	China
No support	14	25
Training content	37	49
iAssist	295	82

To assess the impact of different levels of integrated sustainability support, the sheet metal designs were analysed based on sustainability metrics. For comparability, the metrics were aggregated into three categories: accepted, minor revision, and major revision. This categorization was developed in collaboration with external design experts, who assessed sustainability performance across multiple metrics and mapped typical outcomes to the three categories. Designs rated as accepted were considered fully suitable without changes, while major revision indicated substantial shortcomings. The distribution of these categories across the different support types was then used to compare their effectiveness, with a higher rate of accepted designs interpreted as an indicator of more effective support. Mechanical functionality and manufacturing feasibility were not included in this evaluation and remain the responsibility of the design engineer in subsequent validation steps.

4. Results

The percentage distribution of evaluated sheet metal designs is shown in figure 4, categorized as accepted, minor revision, or major revision, across three support types: no support, training content, and the AI-based iAssist. The results indicate to what extent the level of support influences the sustainability of the submitted designs. A higher proportion of accepted sheet metal designs reflects better alignment with the requirements. Each bar in the chart is segmented by evaluation category, with dark blue representing accepted, medium blue for minor revision, and light blue for major revision. The x-axis displays the percentage scale from 0 % to 100 %, while the y-axis lists the three support types. For the iAssist support (N = 385), 51 % of the designs were categorized as accepted, 31 % required minor revision, and 17 % required major revision. In the training content support (N = 86), 24 % of the designs were accepted, 48 % required minor revision, and 23 % required major revision. The no support (N = 39) showed 5 % accepted designs, 20 % requiring minor revision, and 74 % requiring major revision. Beyond these quantitative results, qualitative analysis of the submitted designs revealed distinct differences. Participants without support tended to remain close to the first idea concept, while those using iAssist explored a broader range of design alternatives. Supported groups also showed a higher tendency to reduce unnecessary features such as weld seams, indicating a stronger consideration of sustainability aspects. These observations complement the quantitative results and provide insight into how different levels of support affect design behavior.

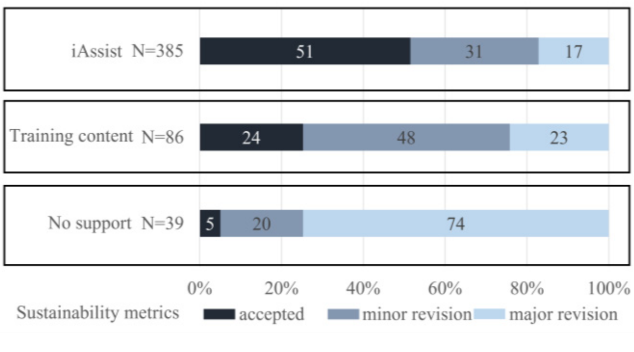

Fig. 4. Three empirical studies conducted between 2022 and 2024 in China and Germany, involving a total of 510 sheet metal designs. The figure shows to what extent different levels of integrated sustainability support, ranging from no support to training content and iAssist, improve the sheet metal design with respect to sustainability metrics.

5. Discussion

The results indicate that higher levels of integrated sustainability support, particularly through the explainable AI-based eco-design support iAssist, lead to more sustainable sheet metal designs. In addition to the higher rate of sustainable accepted designs, supported groups demonstrated broader idea generation, reduced design fixation, and more frequent elimination of unsustainable features such as unnecessary weld seams. Together, these findings suggest that targeted assistance can help overcome common design challenges such as limited idea generation, design fixation, and neglect of sustainability metrics. For example, participants without support often stayed close to reference concepts, while those using iAssist were more likely to explore alternative solutions. The ability to generate multiple ideas and eliminate unnecessary features like weld seams was more evident in supported groups. These findings can be aligned with possible actions, such as providing small methodical steps to encourage creativity and improve spatial visualization. Furthermore, AI-driven recommendation mechanisms can motivate to consider sustainability metrics. The integration of optimization prediction and simultaneous explainability of potential assessments to recommend user-specific training within the iAssist support appears to have positively influenced design alternatives.

However, a current limitation of iAssist is that it does not yet evaluate mechanical functionality or manufacturing feasibility. These aspects must be assessed separately using additional tools and models, and remain the responsibility of the design engineer during the validation process. This reflects a broader challenge in design support systems, where the integration of diverse model types, such as sustainability, mechanical performance, and manufacturability, is still limited. As highlighted by [13,14], many product models in embodiment design lack clear linkability, making it difficult to combine them effectively in a unified support system. Overall, the findings emphasize the importance of structured, adaptive support in guiding engineering designers toward sustainable, mechanical functionable and manufacturable solutions. These insights are valuable for developing future design assistance systems that promote sustainable innovation while maintaining practical feasibility.

6. Conclusion and Outlook

This research demonstrates that systematic and explainable AI-based eco-design support iAssist can significantly enhance the design of sustainable sheet metal products. The evaluated support provides quantifiable sustainability metrics and personalized training content, enabling engineers to recognize and implement more sustainable design alternatives. Empirical studies across different support levels show that iAssist effectively leads to more sustainable sheet metal design. Its consistent generation of a higher proportion of accepted designs confirms its practical value in real-world design settings and live-labs [15–17]. By embedding sustainability directly into the early design phase, iAssist addresses a critical gap in existing engineering workflows. Its iterative and data-driven approach not only improves design quality but also fosters a mindset shift toward sustainable product development. Future work will further refine the AI models, expand the design knowledge base, validate the design content [18,19], and explore integration into broader industrial contexts and design domains beyond sheet metal.

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