Intelligent Human Systems Integration (IHSI 2025), Vol. 160, 2025, 362–371
https://doi.org/10.54941/ahfe1005841

Advancing HCD Through Interdisciplinary Approaches: Insights for Enhancing User-Centric Innovation

Carolin Böhme[1], Dorothea Schneider[2], Mauritz Mälzer[3], Martin Schmauder[1], and Steffen Ihlenfeldt[3]

[1]Technical University Dresden, Faculty of Mechanical Science and Engineering, CIMTT Centre of Production Engineering and Management, 01062, Dresden, Germany
[2]Technical University Dresden, Faculty of Business and Economics, 01062, Dresden, Germany
[3]Technical University Dresden, Faculty of Mechanical Science and Engineering, Chair of Machine Tools Development and Adaptive Controls, 01062, Dresden, Germany

ABSTRACT

The rapid advancement of digitalization and AI presents significant opportunities for small and medium-sized enterprises (SMEs), particularly in manufacturing. However, adoption is often hindered by limited resources, expertise, and scalability issues. This paper introduces an interdisciplinary framework combining engineering, labor sciences, and business informatics to address these challenges. The approach integrates the DMME model for technical rigor, Human-Centered Design for usability, and Action Design Research for iterative development. Through a series of co-design workshops with SME participants, the framework is validated, emphasizing the need for adaptable AI solutions that align with SMEs' unique operational requirements. The findings underscore the importance of bridging technical, human, and business aspects to develop AI systems that enhance user experience, operational efficiency, and digital transformation. Future work aims to refine the approach and extend its scalability for broader implementation.

Keywords: Human-centered design, Action design research, Socio-economic systems, Socio-technical systems, Digital transformation, Cyber-physical production systems

INTRODUCTION

The rapid advancement of digitalization and Artificial Intelligence (AI)-based systems presents both challenges and opportunities for SMEs, particularly in producing companies. AI promises to automate mundane, repetitive tasks, optimize processes, and augment human decision-making. However, for AI to be a practical and effective tool in SMEs, the development approach must go beyond the technology itself to consider the human context in which it will be deployed. Many AI systems fail because they are designed without sufficient consideration of the actual tasks they will assist or replace, leading to poor user adoption and unmet human needs. This paper presents an interdisciplinary approach to integrating AI solutions into engineering systems and business processes that integrates approaches from engineering, labor sciences and business informatics. By combining the specificity of the engineering approach with the context-sensitive and iterative strategies from labor sciences and informatics, we aim to deliver solutions that are customized, user-friendly, and adaptable to the needs of SMEs.

OBSTACLES TO AI SYSTEMS INTEGRATION FOR SMES

Emphasizing the centrality of the human role in AI system development, rather than solely focusing on technical functionality, is essential for creating solutions that effectively enhance user experience and operational efficiency. Despite the transformative potential of AI, several gaps hinder its adoption in SMEs, particularly in producing companies.

Lack of Resources and Expertise. SMEs often have limited technical expertise and financial resources to develop or implement AI systems effectively. Also, the high costs of AI infrastructure (hardware, software, training) are prohibitive for smaller businesses. Another SME-specific problem is the lack of skilled personnel to understand, maintain, and adapt AI solutions over time.

Customization and Scalability Issues. Many AI solutions are built for large corporations, which have the corresponding amount of data and lack the flexibility or scalability needed by SMEs, thus solutions are often not customizable for the unique operational processes of small businesses, leading to poor integration. SMEs require context-specific solutions that are easy to integrate with existing systems.

Limited Awareness and Strategic Planning. Many SMEs lack awareness of the potential benefits of AI for their specific industries or operations and AI is not fully integrated into the strategic planning of SMEs, making digital transformation difficult. General human misconceptions about AI benefits, complexity and risks often lead to resistance or difficulty in adoption or its inadequate prioritization.

Data Access and Management Challenges. As teased above, SMEs frequently lack sufficient quality and volume of data for training AI models. They may not have robust data management systems, leading to fragmented or inconsistent datasets, which impact AI accuracy and performance. Regarding regulations, such as the European AI Act or the GDPR, SMEs often face difficulties in establishing data governance practices, including privacy and security regulations.

User-Centric Design and Usability. Many AI systems are not designed with end-user needs in mind, particularly for non-technical SME employees. This lack of user-friendly interfaces and integration with everyday workflows causes resistance to adoption. SMEs need AI systems that are intuitive and reduce, rather than increase, operational complexity (Wiemer et al., 2023).

Siloed Development Approaches. Traditional AI development often focuses on either technical or business aspects in isolation, without bridging the gap between engineering, business strategy, and human factors. The lack of interdisciplinary cooperation between developers, business leaders, and end-users results in solutions that do not fully meet practical engineering and business needs.

Cyber-Physical Systems (CPS) Integration. In industrial contexts, producing companies face the challenge of not just applying AI to data streams, but also integrating CPS, which merge hardware and software in manufacturing and logistics. This integration requires a blend of mechanical engineering, computer science, and business management expertise. However, the significant investment in hardware, software, and expertise poses a major barrier for SMEs, who often lack the resources to manage the complex interaction between physical and digital systems, leading to potential implementation failures (Lee, 2008).

ESTABLISHED THEORETICAL APPROACHES AND THEIR WEAKNESSES

In developing and adopting AI systems, interdisciplinary approaches are crucial, particularly for small and medium-sized enterprises (SMEs). These methods bridge the gap between technical development and human-centered considerations, ensuring AI systems are functional and well-integrated. However, existing theories often overlook the unique needs of SMEs, assuming access to interdisciplinary expertise and resources that are typically limited in smaller businesses. Moreover, empirical validation in SME contexts remains scarce. For instance, (OECD, 2023) notes that many AI frameworks have been applied in larger organizations but have not yet been thoroughly tested in the unique contexts of SMEs, leaving a critical gap in the literature. Following, some of the key interdisciplinary frameworks are explored that inform the design and implementation of AI in industrial environments, while highlighting their limitations in the SME context.

Sociotechnical Systems Theory (STS). Sociotechnical Systems (STS) theory focuses on the interaction between people and technology within organizational contexts. In its application to AI development, it emphasizes the importance of co-designing AI systems with input from various stakeholders, including engineering, management, and human resources (Gabriel et al., 2022). By considering both the technical and social aspects of AI adoption, STS helps ensure that AI systems are integrated in a way that aligns with human needs and organizational goals. While STS provides a comprehensive framework, it was largely developed with larger enterprises in mind, where resources for interdisciplinary collaboration and system co-design are more readily available. SMEs often lack the internal capacity to bring together such a wide array of disciplines, limiting the practicality of this theory in smaller-scale operations. Furthermore, the collaborative processes advocated by STS can be time-consuming and resource-intensive, making them difficult to apply in SMEs, which are typically more agile and constrained by tighter deadlines and budgets.

Service-Dominant Logic in AI Development. Service-Dominant Logic (SDL) in AI development is an interdisciplinary framework that combines insights from marketing, IT, and organizational science (Vargo & Lusch, 2004). SDL focuses on the co-creation of value between AI developers and users, making it particularly relevant for customer-facing AI systems (Grundner & Neuhofer, 2021). The framework encourages collaboration between developers, business owners, and customers, ensuring that AI solutions deliver value across the entire service spectrum. While SDL emphasizes collaboration, it assumes a level of partnership between AI developers and users that is often not feasible in SMEs due to resource and expertise gaps. Additionally, SDL's heavy reliance on co-creation and continuous feedback loops may not be sustainable in SMEs, which often operate with limited budgets and cannot afford the iterative, resource-heavy development cycles that larger companies can manage.

Transdisciplinary Design Thinking. Transdisciplinary Design Thinking is a collaborative problem-solving approach that draws from disciplines such as design, engineering, business, and social sciences. It emphasizes iterative prototyping and user-centered design, which makes it suitable for developing AI solutions that align with the specific needs of SMEs (Brown, 2008). The iterative nature of design thinking allows for flexible, creative solutions that can adapt to changing business requirements. Although Transdisciplinary Design Thinking promotes flexibility, its iterative and experimental processes can be too resource-intensive for SMEs, which often require faster, more efficient solutions. Moreover, the collaborative aspect of design thinking, which necessitates the involvement of various stakeholders, may be difficult to achieve in SMEs, where employees are often required to take on multiple roles and may not have the time or expertise to participate fully in the design process (Gonera & Pabst, 2019).

Human Factors Engineering. Human Factors Engineering focuses on designing systems that align with human capabilities and limitations. By integrating psychology, ergonomics, and AI design, this approach ensures that AI systems are user-friendly and enhance human productivity. In industrial sectors, particularly those involving manual labor, Human Factors Engineering can help AI systems better assist human workers. While highly valuable, Human Factors Engineering often requires deep expertise in both AI systems and human behavior, which SMEs may not have access to. Moreover, the extensive testing and evaluation required to ensure that AI systems align with human factors can be costly and time-consuming, making it less practical for resource-constrained SMEs (Salvendy, 2012).

THEORETICAL FRAMEWORK

To help overcome the challenges faced by SMEs in the integration of AI systems we suggest an interdisciplinary approach comprising perspectives from engineering, business informatics, and human-centered design. Each discipline brings a complementary lens to AI development and integration:

1. **Engineering procedure models** contribute technical expertise, offering insights into the feasibility of implementing AI systems in production environments. However, engineering alone tends to focus on *what* can be done, without considering the *how* or *why* from a human-centric perspective.
2. **Human-centered design** (**HCD**), rooted in ergonomics and work science, ensures that AI systems are developed in a way that supports workers

by improving usability, reducing cognitive load, and enhancing decision-making. This perspective is crucial for SMEs where employees may have a range of technical skill levels, and the success of AI adoption depends on user acceptance.

3. **Business informatics research design,** Action Design Research (ADR), applied on development and integration tasks provides an iterative, context-sensitive approach for solving complex design quests. ADR emphasizes the importance of evolving not only the solution but also the methodology itself in response to real-world use cases, driving developed solutions towards being adaptable to the specific needs of SMEs. This is particularly relevant for SMEs in the engineering domain, where scalability and flexibility are key to maintaining competitiveness.

By combining these perspectives, the approach ensures that AI development and integration is not purely driven by technological advancements but also by the needs, capabilities, and limitations of the human workforce within the SME context. This interdisciplinary collaboration helps overcome the typical fragmentation between stakeholders, fostering a more holistic view in which AI solutions are developed with both technical and human-centered considerations from the outset.

Thus, the interdisciplinary approach acts as a *unifying framework* that bridges the gap between stakeholders, ensuring that AI solutions are not just technically sound but also aligned with the specific needs and operational realities of SMEs. This fosters more effective communication, better alignment of goals, and ultimately, more successful AI implementations in production companies.

METHODOLOGY

The development of AI systems for small and medium-sized enterprises (SMEs) benefits from a multi-disciplinary framework that combines principles from engineering, work science, and information systems. The methodology described in this paper integrates three key models: the DMME (Data Mining Methodology for Engineering), Human-Centered Design (HCD), and Action Design Research (ADR). Each concept addresses specific challenges associated with AI adoption in SMEs, focusing on the intersection of technical and human factors. This section presents the concepts in detail and describes their practical interaction in interdisciplinary workshops aimed at improving AI system integration and development within SMEs.

The DMME Model (Engineering Science)

The DMME model, adapted from the CRISP-DM (Cross Industry Standard Process for Data Mining), provides a structured methodology for data-driven AI development in engineering. It manages technical complexities by focusing on "what" aspects, such as problem definition, data collection, and solution structuring, ensuring rigor and reliability in industrial settings. However, it falls short on addressing human-centered needs, as it lacks mechanisms for adapting solutions based on user feedback in SMEs. While offering precise guidance for engineering tasks, its case-specific approach does not fully accommodate the social and cognitive needs of users, requiring additional methodologies for usability and refinement (Huber et al., 2019) (Drowatzky et al., 2023).

Human-Centered Design (HCD) (Work Science)

The Human-Centered Design (HCD) approach, based on work science and standards like ISO 9241-210, offers a complementary perspective by focusing on tailoring AI systems to user needs. Emphasizing usability and system integration with human tasks, HCD addresses gaps left by technical models like DMME. Its flexibility is valuable for SMEs, allowing adaptations to specific workflows and resource limitations. The iterative design process, incorporating user feedback, ensures that the final system is both effective and user-friendly. By concentrating on "how" systems integrate into tasks and user interactions, HCD addresses the human and contextual aspects often overlooked in technical approaches (Maguire, 2001).

Action Design Research (ADR) (Information Systems)

Action Design Research (ADR), originally a research design within the field of information systems, provides a development strategy, that focuses on the development of solutions and their iterative revision. Moreover, it encourages the iterative refinement of the methodology itself. Unlike traditional design research, which refines solutions continuously in a single process, ADR adapts development to the interaction context's needs. For SMEs, this means refining both the AI system and the implementation methods. ADR supports a flexible, iterative approach, which is valuable for SMEs with varying requirements. It fosters collaboration between technical developers, business owners, and end-users to ensure practical, sustainable solutions while adapting to evolving needs through feedback-driven iteration (Sein et al., 2011) (Mullarkey & Hevner, 2019).

Workshop Structure and Implementation

The interdisciplinary approach in this paper was implemented through workshops tailored to SME needs, using a co-design format that brought together experts from engineering, work science, and information systems with SME representatives (Becker et al., 2020). Methods like interviews, creativity techniques, interactive external knowledge representation, and feedback loops ensured AI solutions were both technically sound and user-friendly. The provided knowledge was curated in an asynchronous off-site process of knowledge making (Schneider & Kusturica, 2021). The workshops facilitated cross-disciplinary collaboration, integrating insights from DMME, HCD, and ADR, to align technical feasibility with human-centered concerns, ensuring AI systems fit seamlessly into SME operations.

EMPIRICAL VALIDATION: INSIGHTS FROM INITIAL WORKSHOP IMPLEMENTATIONS

The verification workshops conducted with SME participants provided valuable insights into the challenges faced during digital transformation. SMEs, particularly in production industries, highlighted several barriers to AI adoption, such as resource constraints, lack of technical expertise, and difficulty in integrating new technologies into existing workflows. However, initial successes were also noted, including reductions in task complexity, improved employee satisfaction, and gains in operational efficiency.

Every ADR intervention with an SME involved a series of interaction formats with SME representatives according to the relevant roles involved in the integration and development of AI systems in the company. Participants were chosen to represent their various relevant roles in the company, such as managing directors, machine operators and technology developers or service employees. The interaction formats comprised: (A) Surveying and semi-structured interviews, (B) Creativity methods for application potential, (C) Interactive provision of external knowledge representations, (D) Creativity methods for solution potential, (E) Iterative prioritizing and refining (F) Scientific expert feedback and outlook.

Each interaction format contributed by various extent to the obstacles faced by SMEs described in Section 2. Key outcomes from the workshops, summarized in Table 1, emphasized the importance of capturing the individual company characteristics, specifically its constraints and existing infrastructure and organizational background. Furthermore, the interaction of company representatives with each other in finding application potential and its prioritizing proved to be beneficial. The interactive provision of external knowledge was particularly effective in addressing misconceptions and uncertainties (Yasuoka et al., n.d.). The knowledge provision was realized by offering examples of specific engineering procedure model implementations, tailored to be relevant for the individual company. These were interactively communicated in a step-by-step manner within a simplified business game setting. The knowledge input led to an increase in creativity and a more realistic perception of the applicability and potential benefits of AI solutions. When exploring potential AI integration and development solutions, SME representatives recognized the requirement for solutions to be easily integrated into business operations. Moreover, to be considered, any solution must have the ability to deliver value added without requiring an implementation effort exceeding its worth (Wiemer, Conrad, et al., 2023). Further, prioritizing allowed for adaptation to individual constraints while the interaction between various user roles proved to be as helpful and inspiring as controversial during the prioritization phase. Finally, feedback of scientific experts on the commonly derived insights and solutions helped to find context-specific tailored solution ideas and an outlook on how to realize even complex cyber-physical solution approaches.

Table 1. Interaction formats addressing SME obstacles (protocolled by workshop leaders).

Obstacles	Examples	A	B	C	D	E	F
Lack of Resources and Expertise	Constraints in skilled personnel, infrastructure	xxx	x	-	xx	xxx	xx
Customization and Scalability Issues	Context-specific solutions needed, integration with existing systems	xx	x	-	x	-	xxx
Limited Awareness and Strategic Planning	misconceptions about AI complexity, benefits, risks	x	-	xxx	-	xx	xx
Data Access and Management Challenges	data quality and volume, data governance complience	-	-	xx	-	x	xx
User-Centric Design and Usability	need for user-friendly intuitive systems and interfaces	x	-	x	xxx	xx	x
Siloed Development Approaches	gap between engineering, business strategy and human factors	-	xxx	-	x	xxx	-
Cyber-Physical Systems Integration	complex interplay between physical and digital systems	-	xx	xxx	x	xx	xxx

Keys:
(A) Surveying and semi-structured interviews; (B) Creativity methods for application potential; (C) Interactive provision of external knowledge representations; (D) Creativity methods for solution potential; (E) Iterative prioritizing and refining; (F) Scientific expert feedback and outlook
Influence on solvability of obstacle:
- minimal; x moderate; xx substantial; xxx strong

CONCLUSION

The interdisciplinary approach used in this paper addresses significant gaps in AI system development for SMEs. The DMME model, while technically robust, leaves critical usability and contextual gaps that were filled by the HCD approach. HCD ensured that AI systems were adapted to the needs of human users, especially in terms of system interaction and ease of use. Meanwhile, ADR provided a flexible, iterative framework that refined not only the solutions but also the development process, ensuring that the methodology itself evolved alongside the AI systems.

While interdisciplinary collaboration proved to be essential, it also presented certain challenges. The varied objectives and methodologies of the disciplines engineering, work science, and information systems sometimes led to conflicting priorities. For example, technical experts might prioritize system performance, while work scientists focused on usability and user satisfaction. Overcoming these barriers required effective communication and a commitment to integrating insights from all stakeholders.

The methodology described in this paper is not a static framework. Instead, it is designed to evolve continually, shaped by feedback from both users and technical experts. As AI systems are further integrated into SME contexts, the methodology will continue to be refined to ensure it remains adaptable to new challenges and technological developments.

This paper demonstrates that interdisciplinary collaboration is essential for creating AI systems tailored to the needs of SMEs. The integration of engineering science, work science, and information systems has led to the development of a flexible methodology that ensures both technical robustness and user-centric design. The iterative nature of this approach, supported by frameworks such as ADR, HCD, and DMME, ensures that solutions are continuously refined to meet evolving SME needs.

Future work will focus on collecting additional empirical data and evolving the approach further by completing more company interventions acting as model development iterations. The research on optimal interactive knowledge provision and the respective retrieval and preparation process will be intensified, including AI algorithm-based approaches. An especially interesting outlook is the evolvement of the concept into a more scalable approach available to a broader range of participants.

ACKNOWLEDGMENT

This research was funded by "PAL-PerspektiveArbeitLausitz" (funded by The Federal Ministry of Education and Research (BMBF) with funding code 02L19C301), "Demonstrations- und Transfernetzwerk KI in der Produktion" (funded as part of the ProKl-Network, ProKl-Dresden by The Federal Ministry of Education and Research (BMBF) with funding code 02P22A050) and "Sicherer Einsatz KI-gestützter Assistenzsysteme (SKIA)" (funded by the Dieter-Schwarz-Stiftung).

REFERENCES

Becker, F., Meyer, M., Redlich, B., Siemon, D., & Lattemann, C. (2020). Open KMU: Mit Action Design Research und Design Thinking gemeinsam innovieren. HMD Praxis der Wirtschaftsinformatik, 57(2), 274–284. https://doi.org/10.1365/s40702-020-00604-z

Brown, T. (2008). Design Thinking. Harvard Business Review, 86, 84–92, 141.

Drowatzky, L., Wiemer, H., & Ihlenfeldt, S. (2023). Data Mining Suitable Digitization of Production Systems – A Methodological Extension to the DMME. In M. Liewald, A. Verl, T. Bauernhansl, & H.-C. Möhring (Eds.), Production at the Leading Edge of Technology (pp. 524–534). Springer International Publishing. https://doi.org/10.1007/978-3-031-18318-8_53

Gabriel, S., Bentler, D., Grote, E.-M., Junker, C., Wendischhoff, D. M. zu, Bansmann, M., Latos, B., Hobscheidt, D., Kühn, A., & Dumitrescu, R. (2022). Requirements analysis for an intelligent workforce planning system: A socio-technical approach to design AI-based systems. Procedia CIRP, 109, 431–436. https://doi.org/10.1016/j.procir.2022.05.274

Gonera, A., & Pabst, R. (2019). The Use of Design Thinking in Transdisciplinary Research and Innovation Consortia: Challenges, Enablers, and Benefits. Journal of Innovation Management, 7(3), 96–122. https://doi.org/10.24840/2183-0606_007.003_0006

Grundner, L., & Neuhofer, B. (2021). The bright and dark sides of artificial intelligence: A futures perspective on tourist destination experiences. Journal of Destination Marketing & Management, 19, 100511. https://doi.org/10.1016/j.jdmm.2020.100511

Huber, S., Wiemer, H., Schneider, D., & Ihlenfeldt, S. (2019). DMME: Data mining methodology for engineering applications – a holistic extension to the CRISP-DM model. Procedia CIRP, 79, 403–408. https://doi.org/10.1016/j.procir.2019.02.106

Lee, E. A. (2008). Cyber Physical Systems: Design Challenges. 2008 11th IEEE International Symposium on Object and Component-Oriented Real-Time Distributed Computing (ISORC), 363–369. https://doi.org/10.1109/ISORC.2008.25

Maguire, M. (2001). Methods to support human-centred design. International Journal of Human-Computer Studies, 55(4), 587–634. https://doi.org/10.1006/ijhc.2001.0503

Mullarkey, M. T., & Hevner, A. R. (2019). An elaborated action design research process model. European Journal of Information Systems, 28(1), 6–20. https://doi.org/10.1080/0960085X.2018.1451811

OECD. (2023). OECD SME and Entrepreneurship Outlook 2023. OECD. https://doi.org/10.1787/342b8564-en

Salvendy, G. (2012). Handbook of human factors and ergonomics. John Wiley & Sons.

Schneider, D., & Kusturica, W. (2021). Towards a Guideline Affording Overarching Knowledge Building in Data Analysis Projects. Business Information Systems, 49–59. https://doi.org/10.52825/bis.v1i.56

Sein, M. K., Henfridsson, O., Purao, S., Rossi, M., & Lindgren, R. (2011). Action design research. MIS Quarterly, 37–56.

Vargo, S. L., & Lusch, R. F. (2004). Evolving to a New Dominant Logic for Marketing. Journal of Marketing, 68(1), 1–17. https://doi.org/10.1509/jmkg.68.1.1.24036

Wiemer, H., Conrad, F., Lang, V., Boos, E., Mälzer, M., Feldhoff, K., Drowatzky, L., Schneider, D., & Ihlenfeldt, S. (2023). Illustration of the Usable AI Paradigm in Production-Engineering Implementation Settings. In H. Degen & S. Ntoa (Eds.), Artificial Intelligence in HCI (Vol. 14050, pp. 640–661). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-35891-3_40

Wiemer, H., Schneider, D., Lang, V., Conrad, F., Mälzer, M., Boos, E., Feldhoff, K., Drowatzky, L., & Ihlenfeldt, S. (2023). Need for UAI–Anatomy of the Paradigm of Usable Artificial Intelligence for Domain-Specific AI Applicability. Multimodal Technologies and Interaction, 7(3), 27. https://doi.org/10.3390/mti7030027

Yasuoka, M., Nakatani, M., Taoka, Y., & Hamaguchi, N. (2024). Interactivity Matters – A Role of External Representations in Knowledge Transfer During Participatory Design Workshops. Proceedings of the 57th Hawaii International Conference on System Sciences.