SME PRODUCTION RESILIENCE: A FOUR-LAYER AI USE CASE SELECTION APPROACH

DOI
https://doi.org/10.18690/um.fov.4.2026.40

ISBN
978-961-299-152-4

KLAUS MÜLLER, MICHAEL SCHÖPPE, HORST WILDEMANN
Technical University Munich, Research Institute for Corporate Governance, Logistics and Production, Munich, Germany
klaus1.mueller@tum.de, michael.schoeppe@tum.de, sek.bwl@mgt.tum.de

Small and medium sized manufacturers (SME) face recurring disruptions which can be addressed by an increase of resilience. Current solutions based on Artificial Intelligence (AI) offer a possibility to meet requirements in terms of resilience while offering high business efficiency. However, the identification of suitable use cases shows a high complexity due to its innovative character and multiple solutions being introduced in a short time. This paper proposes an approach for early-stage use case identification that combines corporate domains to frame the application context, resilience dimensions to specify the intended effect, and a compact self-assessment of technical and organizational prerequisites. The approach derived to identify use cases is implemented in a web-based IT-demonstrator that guides users through four decision layers and delivers an individualized selection of AI use cases aligned with the SME context and resilience objective. To test comprehensibility, practical plausibility, and usefulness across heterogeneous SME conditions the demonstrator and selection logic were refined and validated with industry experts.

Keywords:
AI use case selection,
production resilience,
SMEs,
implementation readiness,
IT-demonstrator

University of Maribor Press

1 Introduction

Resilience of production systems has gained importance recently due to crises such as COVID-19, international conflicts, and tariffs. Such events can significantly affect businesses and must be assessed by crisis type and duration (Lund et al., 2020). In a crisis, production materials can show volatile prices or even be unprocurable (Bardt, Grömling, & Schmitz, 2022). Resilience addresses these challenges and can be defined as the ability to withstand and recover from disruptions with potential impact on the production processes (Lerch, Jäger, & Horvat, 2022; Luo et al., 2024; Mwangola, 2018). To do so, companies must identify, evaluate and mitigate production risks (Romero, Stahre, Larsson, & Ronnback, 2021).

Resilience originated in material science as the ability to return to an original state after a load. By extension, a resilient production system can anticipate, repel, and recover from disruptions (Lerch et al., 2022; Mwangola, 2018). In contrast to mere robustness, a resilient system goes beyond recovering to its original state by actively adapting to new conditions and transforming underlying processes (Bauer, Böhm, Bauernhansl, & Sauer, 2021). A resilient response unfolds in five phases: preparing, preventing, protecting, responding, and recovering (Kohl et al., 2021; Maier, Puppala, & Oberle, 2024). It thus requires anticipation, robustness, agility, flexibility, adaptivity, and learning (Kohl et al., 2021; Wildemann, 2025).

A resilient production system must therefore fulfil two functions: maintaining production despite disturbances and recovering to a state equal or better than before (Mockenhaupt & Schlagenhauf, 2024; Wildemann, 2025). Disturbances can arise from events such as the pandemic named above. Internal disturbances stem from operational risks such as machine breakdowns, employee illness, or quality defects. Resilience can be actively increased through management approaches such as resilience engineering (Romero et al., 2021; Wenig, Amann, & Wölflick, 2024). Traditional measures focus on redundancies, overcapacities, and safety stocks. These approaches are typically associated with a loss of efficiency in terms of the profitability of a production system by increasing the capital required for a similar output (Ganin et al., 2017). In general, resilience investments should be allocated by expected impact. Artificial Intelligence (AI) opens new possibilities to target measures to increase the resilience of production systems and to overcome the apparent contradiction of resilience and profitability.

AI describes digital systems which can imitate human behavior. Unlike classical digital solutions AI systems can handle unfamiliar situations by relating new tasks to prior knowledge (Seifert et al., 2018). These capabilities allow AI to predict risks and disturbances from available data, strengthening anticipation. Their capacity to process large datasets also can improve transparency over the state of the production system. Building on this, AI can rapidly adapt production plans, increasing agility, flexibility and adaptivity.

Successful AI implementation requires understanding both how AI works and which applications fit a given company's structure. In fact, many companies have already invested heavily in AI but struggle with a lack of returns, data availability or the lack of expertise in their companies (Challapally, Pease, Raskar, & Chari, 2025; IDC, 2025). This paper therefore addresses the research question:

How can companies with internal production systems efficiently identify use cases to increase their production resilience without negatively impacting their profitability?

This paper contributes to the existing literature by providing an approach to implementing AI based on empirical study results particularly focusing on the identification of specific AI use cases. It also offers practitioners a guideline for assessing their own capabilities regarding the implementation of AI use cases building up on case studies from other companies.

2 Theoretical and Technological Foundation

AI relies on statistical models that employ different methods according to the task. AI methods can be differentiated in supervised learning, in which a model is trained to fulfil a specific task on given data, in semi-supervised learning in which the decisions are not fully previously specified and unsupervised learning in which the AI derives conclusions from given data by itself. A leap forward in the application and public reception of AI was achieved by the introduction of generative AI in combination with foundational models. This combination enabled new content to be created through natural language interaction between user and AI in form of human speech. At the same time, the barrier to adopting AI in a business has decreased as the IT expertise required of users has decreased.

2.1 AI in the context of resilience

Building resilience in a company requires addressing multiple interacting dimensions in managing risks. These dimensions include financial, operative, technological, organizational and reputational resilience (Wildemann, 2022). Financial resilience requires sufficient liquidity to cover unexpected debt defaults or sales drops. Operative resilience maintains production stability during supply or demand disruptions, technological resilience covers the ability to adapt digital systems and infrastructure, organizational resilience addresses strategic governance and decision-making capacity in crises, and reputational resilience concerns public perception and ESG compliance. These goals can be operationalized in the concepts of absorption, adaptability, and transformation (Linkov & Trump, 2019; Rudloff, 2022).

Wildemann (2022) describes eight design principles for company resilience (figure 1), which can be related to the capabilities of AI. In a production setting, AI can forecast demand, volumes and market prices to optimize supply chains and pricing (Iseri, Iseri, Chrisandina, Iakovou, & Pistikopoulos, 2025). AI can augment human decision-making by surfacing and evaluating relevant data. It enhances transparency by measuring and analyzing real-time data, increasing resilience by operationalizing internal and external information (Iseri et al., 2025; Rožanec et al., 2023). AI can also predict machine failures. This predictive-maintenance approach identifies actions needed to keep production running while increasing efficiency through the avoidance of unnecessary repairs. Automated quality control aids in receiving direct feedback for production planning, making human controls obsolete. Combining predictive maintenance, quality control and production planning, improves production planning by enriching the accuracy of the approach.

By analyzing large datasets and automated decision-making, AI can identify atypical business deviations (Baryannis, Validi, Dani, & Antoniou, 2019). Given their low cost, AI-based prediction models help to achieve resilience without compromising profitability. The examples show how AI can strategically strengthen resilience of manufacturing companies. Based on expert-interviews, Merhi and Harfouche (2024) evaluated critical success factors to implementing AI based on the Technology-Organisation-Environment framework, resulting in a critical relevance of top management support for successful implementation (Tornatzky & Fleischer, 1990). Improving resilience through AI can therefore be seen as a strategic concern.

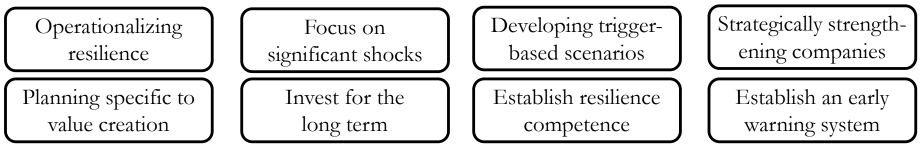

Figure 1: Design principles for increasing resilience
Source: Own depiction related to Wildemann (2022)

The 'invest for the long term' principle reflects that resilience by itself produces value only when a shock occurs. Companies must therefore prepare the required structures before a shock arrives which demands a high degree of foresight and management commitment to invest accordingly. Besides top management support, factors such as perceived compatibility, perceived benefits, data quality, technical experience and complexity also drive successful AI implementation (Merhi & Harfouche, 2024; Schwaeke, Peters, Kanbach, Kraus, & Jones, 2025). Building competence in resilience and AI requires clearer guidance about actual compatibility of possible approaches and the necessary means to achieve a running system. By analyzing external data such as news reports, AI can support the identification of events that may threaten business continuity (Kohl et al., 2021). AI thus enables automated early warning systems. Automating external data evaluation reduces the necessary manual time invest, reducing the cost to increase resilience.

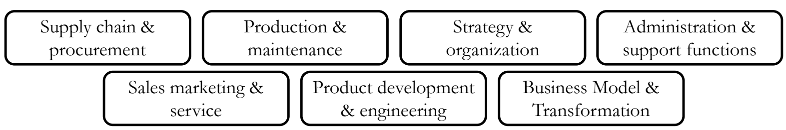

Figure 2: Corporate areas for increasing resilience
Source: Own depiction related to Porter and Millar (1985)

To make resilience actionable, this paper differentiates distinct corporate domains. This functional decomposition follows Porter's value chain logic, which structures firm activities by area of value creation (Porter & Millar, 1985). Based on this, this paper distinguishes the domains: Supply Chain and Procurement; Production and Maintenance; Strategy and Organization; Administration and Support Functions; Sales, Marketing and Service; Product Development and Engineering; Business Model and Transformation. The domains capture the levers of resilience across operational and strategic time frames, ranging from short-term absorption and operational recovery to long-term adaptation and transformation.

Supply Chain and Procurement are critical for production resilience, since disruptions directly affect material availability and production continuity (Nugroho, Santosa, & Khoa, 2025). Production and Maintenance shape resilience through the system's ability to absorb and recover from disruptions. Effective maintenance strategies, especially those that integrate preventive and predictive approaches, reduce unplanned downtime and improve the availability of a system. This enables production to continue during disturbances and recover faster afterwards (Wachter, Beckschulte, Hinrichs, Sohnius, & Schmitt, 2024). Strategy and Organization enhance production resilience by embedding resilience goals into strategic planning, governance, and decision-making. This strengthens the company's ability to anticipate disruptions, allocate resources, and coordinate cross-functional responses (Toro-Gallego, Sapena-Bolufer, Plaza-Navas, & Torres-Pruñonosa, 2025). Administrative and support related processes can improve resilience through reliable management of data, structured failure documentation, and continuous information exchange across organizational levels. Robust digital infrastructure and systematic failure management reduce downtime and support the adaptability during disruptions (Wachter et al., 2024). Sales, Marketing and Service affect operational stability through demand patterns, customer behavior, and market communication, which determine planning reliability and resource utilization. Demand shifts and volatility can destabilize schedules when information is delayed or inaccurate (Ivanov, 2021). Product Development and Engineering play a preparatory role, shaping the product and process data that later determines production stability. Well-prepared engineering data enables production systems to handle variants, process changes, and resource constraints more effectively, building resilience before disturbances occur (Meyer, Hinrichsen, & Niggemann, 2023). Business Model and Transformation improve resilience by establishing adaptability and recovery as principles of the value-creation system. This enables production systems to adapt and recover, rather than merely withstand failures (Reifert et al., 2022).

2.2 Implementation Requirements of AI Use Cases

AI can increase the profitability and resilience of production systems, but companies are limited in the resources they can invest. Many firms also face barriers related to data, capabilities, and management of data, that limit the AI deployment (Kolev-Schaefer et al., 2025). Technical requirements are therefore critical success factors, since they determine which use cases are feasible. In context of production, data availability and data quality are central prerequisites, since model outputs depend directly on the underlying datasets and their preparation (Sánchez, Calderón, & Herrera, 2025). Technical and data readiness are essential for sustained operational success, since AI applications require a solid data and technology foundation (Uren & Edwards, 2023). In manufacturing, quality assurance for AI relevant datasets should address completeness, correctness, consistency, uniqueness, timeliness, and accuracy, because missing or incomplete data can make ML applications unusable or highly error prone (Wiemer, Dementyev, & Ihlenfeldt, 2021).

Beyond technical requirements, assessing organizational prerequisites is equally critical since AI initiatives depend on coordinated decisions about priorities, responsibilities, compliance and change management across the firm (Papagiannidis, Enholm, Dremel, Mikalef, & Krogstie, 2023). AI governance is therefore a central enabling condition. First, explicit leadership support enables prioritization, funding and conflict resolution during implementation (Alzahrani, 2025). Second, AI initiatives must be strategically anchored in alignment with the organization's overarching goals (Prasetyo, Peranginangin, Martinovic, Ichsan, & Wicaksono, 2025). Third, legal and governance readiness requires awareness of regulatory expectations and the ability to translate them into internal rules, responsibilities and control mechanisms for trustworthy implementation (Papagiannidis et al., 2023). Fourth, culture and workforce readiness matter, since adoption can stall when employees perceive AI as threatening, making transparent communication and education essential (Alzahrani, 2025).

3 Methodology

This research is part of the publicly funded research project ResProKI (IGF 01IF23407 N / 1, October 2024-September 2026). This paper is passed on a sequential multi-method research design to identify, structure, and validate AI use cases for strengthening production resilience in SMEs. The work follows the Design Science Research Methodology, which proceeds through problem identification, definition of solution objectives, design and development, demonstration and evaluation (Peffers, Tuunanen, Rothenberger, & Chatterjee, 2007). First, an evidence base was built by analyzing documented case material and conducting a structured literature review (vom Brocke et al., 2009). The review combined the search topics artificial intelligence, machine learning, production resilience and AI use case identification. In parallel, a market screening of available AI solutions and vendors was conducted in August 2025 to identify practice-oriented application clusters and implementation patterns. These inputs were consolidated into an initial use-case inventory and a preliminary mapping logic linking use cases to corporate domains and resilience dimensions. Second, qualitative expert interviews with SME representatives and AI practitioners were conducted as problem centered interviews to identify resilience related pain points and constraints. The findings were consolidated into a structured problem perspective and served to derive and specify candidate use cases and assessment criteria. Third, the design and development phase involved implementing the mapping logic and selection procedure in an IT-demonstrator, thereby translating the conceptual approach into an operational artefact. Demonstration was embedded in this phase by applying the demonstrator to representative inputs and use case scenarios to verify the internal consistency of the decision layers and to check whether the generated shortlists were plausible before conducting the formal evaluation.

The demonstrator and its underlying selection logic were validated within three sessions of focus group interviews with SME representatives (n=5 on 08.07.2025; n=8 on 15.01.2026; n=5 on 16.03.2026). They were complemented by individual expert interviews (n=6) conducted from August 2025 to March 2026. The discussions focused on plausibility, clarity, and applicability across heterogeneous SME contexts.

4 Design and Development

The artefact developed is a web-based IT-demonstrator that operationalizes the selection logic into a guided procedure for SMEs. Its purpose is to reduce ambiguity in early-stage use case exploration by combining contextual scoping with a structured assessment of prerequisites. Instead of producing a generic catalogue, the demonstrator links use cases to the user's operational context and filters them against the organization's current ability to implement data driven applications in a stable manner. The selection logic follows a four-step procedure. Users first select the corporate domain in which resilience shall be strengthened, namely Supply Chain and Procurement, Production and Maintenance, Strategy and Organization, Administration and Support Functions, Sales Marketing and Service, Product Development and Engineering, or Business Model and Transformation.

They then select the intended resilience dimension, namely financial, operative, technological, organizational, or reputational resilience. Based on this contextual framing, the demonstrator captures technical and organizational prerequisites through a self-assessment that reflects the company's internal maturity for the specified criteria. Among the technical prerequisites, users have to evaluate the availability of data including the evaluation of whether data is collected in central hubs. As the second criterion, the availability of a digital infrastructure in the company is evaluated. The last technical prerequisite is the availability of digital technologies in a company and its use. On the side of the organizational prerequisites, users assess: management support for introducing digital technologies, the strategic anchoring of AI to increase resilience; knowledge of applicable legal frameworks and employee and cultural support for adopting digital technologies. As the presented evaluation is based on a qualitative assessment, each criterion is rated on a three-level scale from scarcely fulfilled to fully fulfilled and mapped to numeric values from 1 to 3, which are aggregated across criteria to form technical and organizational prerequisite scores. The three-point scale was chosen for ease of use: it lets users benchmark internal prerequisites against peers easily as 'better,' 'average,' or 'weaker without requiring finer-grained distinctions. The combined scores position the company in a 2x2 matrix that classifies use cases as low- or high-requirement on each axis enabling a prerequisite-based preselection of candidates. In the assessment, the technical layer focuses on whether the company has the data basis and digital infrastructure required for AI use cases, in particular systematic data capture, accessible and consistent information flows across systems, and a sufficiently mature baseline of digital tooling in daily operations. The organizational layer captures whether a technically feasible use case can be implemented and sustained. It assesses whether digital initiatives are supported by organizational policy and governance, whether AI is anchored as a strategic topic rather than treated as isolated experimentation, whether legal and compliance implications are sufficiently understood to manage data protection and regulatory requirements, and whether the organizational culture supports adoption of new tools and changes in established work routines. Both prerequisite assessments use the same compact ordinal scale, supporting structured reflection, comparability across companies, and the derivation of an overall readiness profile. From the combined profile, the demonstrator produces a shortlist of use cases that match the selected context and are consistent with the assessed prerequisites.

5 Evaluation

The logic as a basis for the web-based IT-demonstrator implementing the selection logic, was validated based on a static mock-up in an application oriented evaluation following the DSRM to examine its applicability and practical usefulness in industrial settings (Peffers, Tuunanen, Rothenberger, & Chatterjee, 2007; Ulrich, 1981). Accordingly, the evaluation was conducted with SME representatives from the fashion and food industries, metalworking industry, the packaging industry, and supplier industries for mechanical engineering and production technology, using focus group interviews and individual interviews (Mayer, 2013). The focus groups reviewed the overall logic of the approach, including the selection procedure and the clarity of criteria and scales, with a focus on completeness and practical plausibility. Within the workshop, the participants applied the demonstrator's prerequisite criteria to their companies, providing application-oriented data on their own technical and organizational readiness. Regarding the technical requirements, data capture was rated predominantly mid-scale, with companies describing production and inventory data as distributed across multiple sources and partially maintained in parallel spreadsheets. At the same time, a smaller subset reported a consolidated ERP environment with structured cross-departmental access. On the organizational side, awareness of legal frameworks showed the widest spread, ranging from unclear internal responsibilities and missing AI guidelines (with the EU AI Act and data protection named as central uncertainties) to established processes supported by external advisors. Cultural acceptance ranged similarly from resistance to digital change to high openness, with adoption depending strongly on visible benefits in daily work and accompanying training formats. In a second step, the logic for the demonstrator was assessed in semi structured individual interviews with SME experts, focusing on usability, the clarity and perceived transparency of the guided procedure, and the usefulness of the generated shortlist (Dicicco-Bloom & Crabtree, 2006). After applying the feedback from the initial logic validation, the demonstrator was implemented and evaluated with a focus group of SME experts to validate the practical feasibility of implemented decision layers under realistic user interaction.

The use case catalogue behind the IT-Demonstrator helps SMEs to efficiently identify suitable use cases by pre-selecting candidates and summarizing each one's functionality, goals and benefits, and technical and organizational requirements. By comparing the achievable benefits with the requirements, SME-representatives can easily identify the viability of the use case including the potential impact regarding the efficiency and resilience impact. During the pre-evaluation of the AI use-cases it was identified that most of these cases were aimed at an efficiency increase while positively impacting the resilience factors at the same time. These effects are shown as use case summary presented to SME representatives in the IT-Demonstrator.

6 Discussion

In the literature, multiple papers were identified which give an overview over potential use cases of AI in the production (e.g. Toorajipour, Sohrabpour, Nazarpour, Oghazi, & Fischl, 2021) grouping AI use cases according to implementation area or AI methodologies. Early-stage exploration of AI use cases for production resilience benefits from a structured decision logic that includes application context, intended resilience effect, and implementation prerequisites. By combining corporate domains and resilience dimensions, the approach specifies the solution space in a targeted way by surfacing use case candidates that fit the company's individual context and resilience objective, rather than presenting generic AI options. The collected use cases were grouped according to the prerequisites and the capability assessment or potential users. The prerequisite assessment structures the solution space by indicating which candidates are plausible under the organization's current technical and organizational conditions, thereby supporting follow up feasibility work. In practice, the IT-demonstrator provides a reusable entry point to offer SMEs additional context specific use cases and to generate an individualized shortlist before committing resources to detailed evaluation and implementation planning. The central benefit lies in structured approach to finding feasible AI applications: the catalogue leads employees to comparable, context-specific examples and provides reference points from which further applications can be derived through analogical transfer in their own operational environment. By replacing abstract technology discussions with concrete use cases, the demonstrator lowers the threshold for initiating AI projects. For research, the paper contributes an operational mapping logic between domains, resilience dimensions, and readiness criteria implemented in a usable demonstrator.

Limitations of the presented work can be found in the fact that no practical implementation of the collected use cases was executed during the project to verify the suitability of the proposed solutions for the company representative using the IT demonstrator. However, it was mentioned by the participants of the validation focus group that the use cases in the current state can be used as an inspiration for employees identifying potential use cases. At the same time, the participants mentioned an additional limitation that an enrichment of the available information would be desirable to include company internal information regarding the success of a use case and suppliers which can be re-used by different departments.

The evaluation focused on usability and practical plausibility and did not measure implementation outcomes in operational deployments. Future work should involve longitudinal testing of the demonstrator in SMEs and quantify effects on the quality of decisions for use cases and the following implementation success. Furthermore, it should extend the approach from guidance at the identification of use cases to quantified evaluation by integrating cost-benefit logic. Additionally, the mapping logic should be refined through broader empirical applications, including cross-industry validation and updates to reflect emerging AI solution classes.

7 Conclusion

This paper developed a four-layer approach for identifying AI use cases that can support production resilience in SMEs. The approach combines corporate domains, resilience dimensions and technical as well as organizational requirements to narrow a set of possible AI applications to a context specific shortlist. By implementing this logic in a web-based IT demonstrator, the study provides a structured entry point for SMEs that need to explore AI opportunities but face limited resources and different implementation conditions.

The main contribution lies in shifting early use case exploration from a generic technology search to a guided selection process based on resilience objectives and readiness criteria. The evaluation indicates that the demonstrator is understandable and practically plausible as a first step before detailed investment assessments.

This article was written as a part of the project "Concept of a resilient and efficient production system by using Artificial Intelligence in SME", which was funded by the Federal Ministry for Economic Affairs and Energy under the reference IGF 01IF23407 N / 1

References

Alzahrani, S. (2025). Assessing artificial intelligence and advanced analytics adoption: A technological, organizational, and environmental perspective. *Edelweiss Applied Science and Technology*, *9*(7), 312–325. https://doi.org/10.55214/25768484.v9i7.8567

Bardt, H., Grömling, M., & Schmitz, E. (2022). Wirtschaftliche Folgen des Ukraine-Krieges: Zunehmende Belastungen für die deutsche Wirtschaft. *IW-Report.*

Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: state of the art and future research directions. *International Journal of Production Research*, *57*(7), 2179–2202. https://doi.org/10.1080/00207543.2018.1530476

Bauer, D., Böhm, M., Bauernhansl, T., & Sauer, A. (2021). Increased resilience for manufacturing systems in supply networks through data-based turbulence mitigation. *Production Engineering*, *15*(3-4), 385–395. https://doi.org/10.1007/s11740-021-01036-4

Challapally, A., Pease, C., Raskar, R., & Chari, P. (2025). *The GenAI Divide: State of AI in Business 2025.*

Dicicco-Bloom, B., & Crabtree, B. F. (2006). The qualitative research interview. *Medical Education*, *40*(4), 314–321. https://doi.org/10.1111/j.1365-2929.2006.02418.x

Ganin, A. A., Kitsak, M., Marchese, D., Keisler, J. M., Seager, T., & Linkov, I. (2017). Resilience and efficiency in transportation networks. *Science Advances*, *3*(12), e1701079.

IDC (2025). *CIO Playbook 2025: It's Time for AI-nomics.*

Iseri, F., Iseri, H., Chrisandina, N. J., Iakovou, E., & Pistikopoulos, E. N. (2025). AI-based predictive analytics for enhancing data-driven supply chain optimization. *Journal of Global Optimization.* Advance online publication. https://doi.org/10.1007/s10898-025-01509-1

Ivanov, D. (2021). Supply Chain Viability and the COVID-19 pandemic: a conceptual and formal generalisation of four major adaptation strategies. *International Journal of Production Research*, *59*(12), 3535–3552. https://doi.org/10.1080/00207543.2021.1890852

Kohl, H., Buß, D., Gebauer, H., Glawar, R., Heller, T., Klan, S., . . . Wilms, M. (2021). *White Paper »RESYST« – Resiliente Wertschöpfung in der produzierenden Industrie – innovativ, erfolgreich, krisenfest.* München: Fraunhofer-Gesellschaft e. V.

Kolev-Schaefer, G., Matthes, J., Schaefer, T., Schmitz, E., Weber, B., & Schmitz-Brieber, J. (2025). *Resilienz der deutschen Lieferketten nach der Zeitenwende: Studie des EPICO KlimaInnovation e.V. in Zusammenarbeit mit dem Institut der deutschen Wirtschaft.* Berlin/Köln.

Lerch, C., Jäger, A., & Horvat, D. (2022). *Resilient in der Krise: Bedeutung von Industrie 4.0 und Lean Management während der COVID-19 Pandemie.* Fraunhofer ISI. https://doi.org/10.24406/PUBLICA-341

Linkov, I., & Trump, B. D. (2019). *The science and practice of resilience.* Springer.

Lund, S., Manyika, J., Woetzel, J., Barriball, E., Krishnan, M., Alicke, K., . . . Hutzler, K. (2020). Risk, resilience, and rebalancing in global value chains. Retrieved from https://www.mckinsey.com/capabilities/operations/our-insights/risk-resilience-and-rebalancing-in-global-value-chains, last accessed 18.02.2026

Luo, X., Kang, K., Lu, L., Yu, C., Li, C., Li, B., . . . Zhou, Y. (2024). Resilience evaluation of low-carbon supply chain based on improved matter-element extension model. *Plos One*, *19*(4), e0301390.

Maier, F. A., Puppala, S., & Oberle, M. (2024). Artificial Intelligence Applications for Resilience in Manufacturing — A Systematic Literature Review, 778–784. https://doi.org/10.1109/ICAIIC60209.2024.10463234

Mayer, H. O. (2013). *Interview und schriftliche Befragung*. Oldenbourg Wissenschaftsverlag. https://doi.org/10.1524/9783486717624

Merhi, M. I., & Harfouche, A. (2024). Enablers of artificial intelligence adoption and implementation in production systems. *International Journal of Production Research*, *62*(15), 5457–5471. https://doi.org/10.1080/00207543.2023.2167014

Meyer, F., Hinrichsen, S., & Niggemann, O. (2023). How to Generate Assembly Instructions with Robotic Process Automation. In AHFE International (Ed.), *AHFE International, Human Interaction & Emerging Technologies (IHIET 2023): Artificial Intelligence & Future Applications* (pp. 629–638). AHFE International. https://doi.org/10.54941/ahfe1004070

Mockenhaupt, A., & Schlagenhauf, T. (2024). *Digitalisierung und Künstliche Intelligenz in der Produktion*. Wiesbaden: Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-41935-6

Mwangola, W. (2018). Conceptualizing Supply Chain Resilience: An Alternative Dynamic Capabilities Perspective. *American Journal of Management*, *18*(4), 76–88. https://doi.org/10.33423/ajm.v18i4.186

Nugroho, A., Santosa, B., & Khoa, T. M. (2025). The Role of Supply Chain Resilience in Enhancing Operational Efficiency among Manufacturing SMEs. *Journal of Economics and Management*, *3*(2), 34–41. https://doi.org/10.70716/ecoma.v3i2.234

Papagiannidis, E., Enholm, I. M., Dremel, C., Mikalef, P., & Krogstie, J. (2023). Toward AI Governance: Identifying Best Practices and Potential Barriers and Outcomes. *Information Systems Frontiers : A Journal of Research and Innovation*, *25*(1), 123–141. https://doi.org/10.1007/s10796-022-10251-y

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A Design Science Research Methodology for Information Systems Research. *Journal of Management Information Systems*, *24*(3), 45–77. https://doi.org/10.2753/MIS0742-1222240302

Porter, M. E., & Millar, V. A. (1985). How Information Gives You Competitive Advantage. *Harvard Business Review*, *63*(4), 149–160.

Prasetyo, M. L., Peranginangin, R. A., Martinovic, N., Ichsan, M., & Wicaksono, H. (2025). Artificial intelligence in open innovation project management: A systematic literature review on technologies, applications, and integration requirements. *Journal of Open Innovation: Technology, Market, and Complexity*, *11*(1), 100445. https://doi.org/10.1016/j.joitmc.2024.100445

Reifert, R.-J., Krawczyk-Becker, M., Prenzel, L., Pavlichkov, S., Khatib, M. A., Hiremath, S. A., . . . Sezgin, A. (2022). Toward Resilience in Mixed Critical Industrial Control Systems: A Multi-Disciplinary View. *IEEE Access*, *10*, 124563–124581. https://doi.org/10.1109/ACCESS.2022.3224425

Romero, D., Stahre, J., Larsson, L., & Ronnback, A. O. (2021). Building Manufacturing Resilience through Production Innovation. In *2021 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)* (pp. 1–9). IEEE. https://doi.org/10.1109/ICE/ITMC52061.2021.9570204

Rožanec, J. M., Novalija, I., Zajec, P., Kenda, K., Tavakoli Ghinani, H., Suh, S., . . . Soldatos, J. (2023). Human-centric artificial intelligence architecture for industry 5.0 applications. *International Journal of Production Research*, *61*(20), 6847–6872. https://doi.org/10.1080/00207543.2022.2138611

Rudloff, B. (2022). Wirtschaftliche Resilienz: Kompass oder Catchword? Welche Fallstricke und Folgeeffekte die EU im Krisenmanagement beachten muss. *2747-5115*.

Sánchez, E., Calderón, R., & Herrera, F. (2025). Artificial Intelligence Adoption in SMEs: Survey Based on TOE–DOI Framework, Primary Methodology and Challenges. *Applied Sciences*, *15*(12), 6465. https://doi.org/10.3390/app15126465

Schwaeke, J., Peters, A., Kanbach, D. K., Kraus, S., & Jones, P. (2025). The new normal: The status quo of AI adoption in SMEs. *Journal of Small Business Management*, *63*(3), 1297–1331. https://doi.org/10.1080/00472778.2024.2379999

Seifert, I., Bürger, M., Wangler, L., Christmann-Budian, S., Rohde, M., Gabriel, P., & Zinke, G. (2018). Potenziale der künstlichen Intelligenz im produzierenden Gewerbe in Deutschland. Retrieved from https://www.bmwk.de/Redaktion/DE/Publikationen/Studien/potenziale-kuenstlichen-intelligenz-im-produzierenden-gewerbe-in-deutschland.pdf?__blob=publicationFile&v=19

Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research*, *122*, 502–517. https://doi.org/10.1016/j.jbusres.2020.09.009

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation. Issues in organization and management series*. Lexington, Mass.: Lexington Books.

Toro-Gallego, C., Sapena-Bolufer, J., Plaza-Navas, M.-A., & Torres-Pruñonosa, J. (2025). The Science of Organisational Resilience: Decoding Its Intellectual Structure to Understand Foundations and Future. *Administrative Sciences*, *15*(10), 404. https://doi.org/10.3390/admsci15100404

Ulrich, H. (1981). Die Betriebswirtschaftslehre als anwendungsorientierte Sozialwissenschaft. In M. Geist & R. Köhler (Eds.), *Die Führung des Betriebes: Curt Sandig zu seinem 80. Geburtstag gewidmet* (1-23). Stuttgart: Poeschel.

Uren, V., & Edwards, J. S. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management*, *68*, 102588. https://doi.org/10.1016/j.ijinfomgt.2022.102588

Vom Brocke, J., Simons, A., Niehaves, B., Riemer, K., Plattfaut, R., & Cleven, A. (2009). Reconstructing the Giant: On the Importance of Rigour in Documenting the Literature Search Process. *Proceedings of the European Conference on Information Systems*. (17).

Wachter, C., Beckschulte, S., Hinrichs, M. P., Sohnius, F., & Schmitt, R. H. (2024). Strategies for Resilient Manufacturing: A Systematic Literature Review of Failure Management in Production. *Procedia CIRP*, *130*, 1393–1402. https://doi.org/10.1016/j.procir.2024.10.257

Wenig, C., Amann, A., & Wölflick, M. (2024). Resilienz in globalen Produktionsnetzwerken. *Zeitschrift Für Wirtschaftlichen Fabrikbetrieb*, pp. 171–175.

Wiemer, H., Dementyev, A., & Ihlenfeldt, S. (2021). A Holistic Quality Assurance Approach for Machine Learning Applications in Cyber-Physical Production Systems. *Applied Sciences*, *11*(20), 9590. https://doi.org/10.3390/app11209590

Wildemann, H. (2022, May 16). Resilienz wird zur Kernkompetenz. *Frankfurter Allgemeine Zeitung*, p. 18.

Wildemann, H. (2025). *Resiliente Unternehmensführung: Leitfaden zur Krisenbewältigung und Transformation von Unternehmen* (4th ed.). München: TCW Transfer-Centrum für Produktions-Logistik und Technologie-Management GmbH & Co. KG.