Process Chain for Artificial Intelligence-Based Demand Forecasting and Procurement Scheduling

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Abstract: This position paper introduces a conceptual general process chain for leveraging artificial intelligence (AI) in demand prediction and procurement scheduling for small and medium-sized enterprises (SME). While AI offers significant advantages, such as reducing inventory costs, improving delivery reliability, and optimizing logistics, its adoption in SME is hindered by limited expertise, restricted access to AI tools, and psychological barriers like trust and acceptance. The proposed framework integrates probabilistic modeling, clustering algorithms, feature extraction methods and temperature scaling to enhance prediction accuracy and efficiency. By aggregating demand forecasts, the system enables risk-adjusted and cashflow-optimized scheduling. A preliminary result is presented, demonstrating robust predictions within confidence intervals. While the findings are preliminary, this paper highlights the transformative potential of AI in SME scheduling and outlines future research directions, including model optimization and the integration of explainable AI methods to further enhance traceability and user acceptance.

1 INTRODUCTION

The field of artificial intelligence (AI) has emerged as a pivotal technology for numerous automated systems and data-driven algorithms, offering significant potential for enhancing business processes across various sectors, including large corporations and small- and medium-sized enterprises (SME). According to an expert survey, the foremost opportunities for AI in SME are projected to lie in the domains of optimizing distribution and logistics and enhancing process efficiency (Lundborg et al., 2023; WIK GmbH, 2019). While the processing of goods can vary significantly depending on the specific industry, many procurements and scheduling processes in the manufacturing industry maintain a high degree of similarity. These processes are often driven by factors such as market conditions, order volume, and company-specific circumstances. The overarching objective of procurement scheduling is to optimize service quality, particularly delivery reliability while minimizing capital expenditures, resource utilization and inventory holding costs. While the prioritization of these factors varies across individuals, their overall relevance remains consistent across all domains. The economic activity of the manufacturing industry is defined as the treatment or processing of products for the purpose of manufacturing or refining products. Procurement planning and organization is a prerequisite for the value creation process. In the context of SME, procurement planning often consists of a separate department that regulates procurement depending on demand. The central task is to define the order quantity and the order time and to organize the transport to some extent. In SME, this process is predominantly executed manually, relying on employees' experiential knowledge. However, this experiential knowledge is vulnerable to fluctuation when employees depart from the company. Moreover, complex issues such as market fluctuations or demand variations may not be fully integrated into employees' experiential knowledge. Large volumes of data accumulate in the planning and

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purchasing departments, which are often incomplete, inaccessible, or underutilized. The advent of technological progress, the proliferation of data, and the emergence of sophisticated algorithms in the big data domain have rendered extensive analyses and models viable tools for process optimization in procurement scheduling. Given the capacity of planners to consider a limited amount of data during the decision-making process, the development of prediction models and efficient algorithms for data preparation and feature extraction is imperative to optimize processes (Allal-Chérif et al., 2021; Baryannis et al., 2019).

The integration of AI into various sectors of industry and research has been a subject of considerable interest in recent years. According to a McKinsey report from 2023, the global potential of AI is 17.1 to 25.6 trillion dollars (roughly 20% of global GDP), making it a significant economic opportunity in today's economic landscape (Chui et al., 2023). The effectiveness of AI in the domain of supply chain management has been a subject of notable attention (McKinsey & Company, 2021). However, the implementation of AI in SME is hindered by several obstacles, primarily the lack of specialized expertise and the challenges in accessing AI as a service (WIK GmbH, 2019). While prominent companies successfully develop and utilize AI services, such as *Forecast Pr*o (Business Forecast Systems, Inc., 2025), and proprietary AI solutions to enhance their own processes, there is a paucity of interest in disseminating this knowledge to the public.

The primary benefit of the framework to be developed lies in the reduction of stock levels and the increase in delivery reliability through the use of AI, especially for SME. While the economic benefit of reducing stock can be quantified using a capital replacement rate, the economic benefit of increasing delivery reliability is difficult to quantify. An increase in delivery reliability has a positive effect on the expansion, stability, and interdependence of business relationships. The successful implementation of AI in supply chain management has been shown to result in a 15% reduction in logistics costs, a 35% decrease in stock levels, and a 65% improvement in service quality (McKinsey & Company, 2021). A recent study by Samuels confirms that the integration of AI into supply chain management improves demand forecasting, inventory optimization and decision-making. This leads to lower inventory levels, cost savings and higher delivery reliability, as AI enables accurate forecasting, minimizes stock-outs and reduces excess inventory (Samuels, 2024).

Global economic uncertainties and supply chain disruptions in recent years have increased the need for smart warehousing systems. Reports such as the OECD SME and Entrepreneurship Outlook show that SME worldwide are struggling with supply bottlenecks and inefficient warehousing strategies, resulting in high storage costs and limited flexibility (OECD, 2023). The use of AI-supported scheduling has the potential to meet these challenges. It facilitates the early recognition of situations such as a drop in demand and the implementation of suitable measures. While the majority of German companies perceive AI as a potential benefit, only a small percentage of companies currently utilize existing methods (Bitkom e. V., 2022). In addition to the challenge of adapting existing solutions to the needs and resources of SME, psychological constructs such as acceptance and trust in AI solutions must increasingly be considered. Studies show that acceptance of AI drops when users see it as a control tool or fear losing decision-making power and jobs. This is especially true in small and medium-sized enterprises, where long-standing routines often make employees less open to change. To foster acceptance of AI, these aspects must be addressed in technical development.

The process chain presented here aims to address the following research questions regarding its application in SME:

- Which combination of data preprocessing, model architecture, and model training maximizes prediction quality?
- To what extent does the proposed process chain, in terms of accuracy, outperform established forecasting models such as ARIMA and Prophet?
- How does AI-supported procurement scheduling impact costs, stock levels, inventory turnover time, and delivery reliability?

2 STATE OF THE ART

Baryannis et al. (Baryannis et al., 2019) highlight the potential of AI in supply chain risk management but point out a lack of research on proactive and predictive AI applications, especially regarding decision-making, prediction methods, and the integration of different AI technologies. Their findings emphasize the need for further investigation in these areas. For instance, Venkatesan, and Goh (Venkatesan & Goh, 2016) developed a multi-criteria mixed integer linear program (MILP) model to identify the optimal selection of suppliers and the allocation of order quantities under the risk of disruption. The findings indicate that the likelihood of supplier default exerts a more substantial influence on the anticipated aggregate expenditures compared to the suppliers' adaptability and the ensuing loss expenses. Pareto-optimal solutions facilitate the assessment of a diverse array of decision alternatives. Nevertheless, the authors highlight several limitations, including those pertaining to deterministic demand or unchanging purchase costs, underscoring the necessity for further research to elucidate these domains. A comparison of different AI-based forecasting methods to improve the accuracy of demand forecasting in supply chains shows that the use of artificial neural networks significantly improves the accuracy of demand forecasting for intermittent demand (Amirkolaii et al., 2017). In the context of SME Wong et al. (Wong et al., 2024) demonstrated the benefits of AI-based risk management in terms of improving business continuity through improved response to changes caused by disruptions.

This paper aims to address the existing research gaps by developing a software process chain for combining probabilistic AI predictors, thereby combining the advantages of big data and machine learning with individual prioritizations. This integration process serves to reduce risk and enhance traceability for the user. Despite the limited attention devoted to human factors in the introduction and utilization of AI applications in recent years, these factors have gradually emerged as a focal point of research interest. However, a more comprehensive understanding of influencing factors such as trust, acceptance, and other psychological factors, which have proven to be key factors for success in the interaction with other technologies and have already been mapped in various models, is still lacking (Choung et al., 2023; Davis, 1989; Manchon et al., 2021). In addition to AI-specific aspects such as representation and the degree of machine intelligence (i.e., its capabilities), findings in the area of trust highlight the relevance of antecedents that shape the cognitive and emotional trust of users. These include the tangibility, transparency, reliability, and immediacy of AI applications, together with the role of anthropomorphism. Explainability has been identified as another pivotal factor influencing trust in AI applications (Ferrario & Loi, 2022). However, the extant empirical findings are subject to certain limitations, including small samples, cross-sectional observations, and experimental studies with constraints on field environments. The samples considered also differ considerably, impeding the attainment of generalizability. Nevertheless, enhancing our understanding of these phenomena appears to be of paramount importance, particularly in the context of SME with limited staffing and lower levels of specialization.

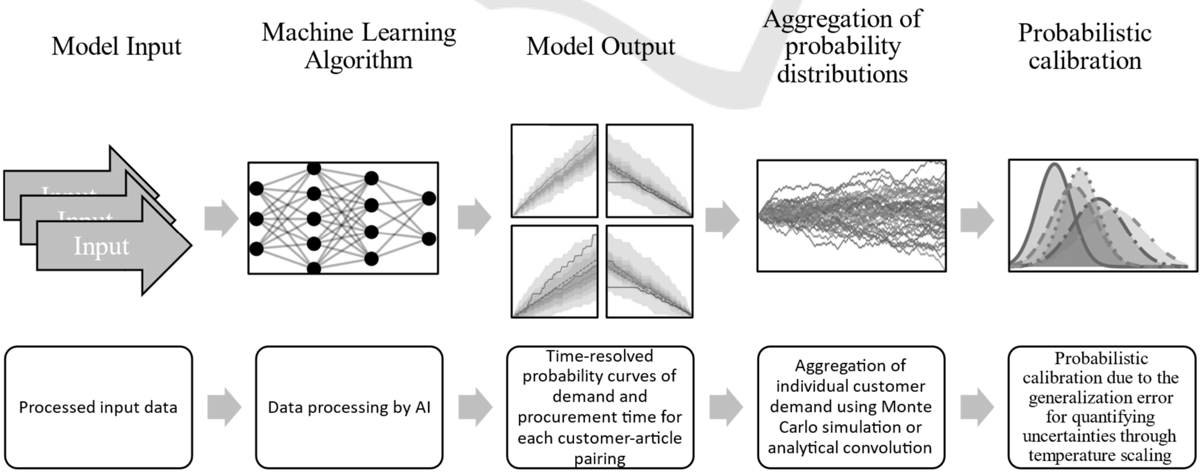

Figure 1: Process chain for predicting customer requirements and procurement times.

3 METHODOLOGY

For developing the software framework, we focus on an exemplarily SME, which is at the center of a network of suppliers and customers. On the supplier side, the procurement time as a function of the unit quantity, and on the customer side, the quantity of demand as a function of time are particularly relevant for the scheduling tasks. There are often only a limited number of data points available for individual customers during the training period. Therefore, we propose to train a machine learning algorithm not for each individual customer, but to use a consolidated model for all customers and all articles. Specific customer and item parameters are then fed into the machine learning algorithm as input. The prediction for item demand can thus be made for each individual customer and then aggregated at component level.

Figure 1 illustrates the process chain from data input, through the machine learning algorithm, to the processed model output. Each step of the process chain will be presented in the following:

Model Inputs

All available and potentially relevant data should be initially used as input variables. A post-analysis, for example using SHapley Additive exPlanations (SHAP) (Lundberg & Lee, 2017), makes it possible to evaluate the influence of the input variables on the target variables. By neglecting less relevant inputs, model complexity can be reduced and efficiency increased. The following model inputs, listed in Table 1, are initially and exemplarily used for prediction.

Table 1: Description of the input variables.

Input	Description	Format
Customer	Since the model represents the demand of all customers within an organizational unit, the customer identity is provided as a unique categorical variable.	One-hot vector
Article	Since the model represents the demand of all articles within an organizational unit, the article identity is provided as a unique categorical variable.	One-hot vector
Customer group	Customers within an organizational unit are typically grouped. This grouping is included in the model as a categorical variable.	One-hot vector
Article group	Articles within an organizational unit are typically grouped. This grouping is included in the model as a categorical variable.	One-hot vector
Historical demand …	Historical demand contains information on patterns, trends, and seasonality. It can be derived from actual deliveries and is provided to the model at three different levels:	
… on customer and article level	Historical demand for the specific customer and the specific article.	Numerical vector
… on customer and article level	Historical demand of the specific customer for all other articles purchased.	Numerical vector
… on customer level of the article	Historical demand of all other customers who purchase the specific article.	Numerical vector
Order frequency	Number of times a customer has ordered an article within a defined period.	Numerical scalar
Average order quantity	Mean order quantity of an article for a specific customer within a defined period.	Numerical scalar
Prediction timestamp	Cyclic encoding of the time in the year.	Numerical vector
Start-of-Production (SoP)	Difference between the SoP and the prediction timestamp.	Numerical scalar
Demand announcements	In certain organizational units, demand is announced in advance. In this case, the VDA4905 standard has been established. Both current and revised announcements are included in the model.	Sparse array
Customer reliability	Based on historical demand announcements and actual demand, the reliability of the announcements can be quantified numerically.	Sparse array
External indices	Publicly available indices provide information on global economic conditions, industry trends, and logistics factors.	Numerical vector

Machine Learning Algorithms – Design of Experiment

At the center of the proposed process chain is an AI-based model that aims to map the relationship between input and output data as accurate as possible and has the highest possible generalization capability. Established methods for trend prediction such as the “Autoregressive Integrated Moving Average” (ARIMA) (Shumway & Stoffer, 2017) and the open source library Prophet (Taylor & Letham, 2018) are initially used as a baseline. A central aspect of the research question is the comparative performance analysis between conventional methods and machine learning based models. In order to achieve a high model quality, a systematic test matrix is applied to the task and examined with regard to its suitability. The overall structure is illustrated in Figure 2.

Both customers and articles can exhibit similar or contrasting patterns in terms of their input/output behavior, which are systematically analyzed as part of the feature extraction process by forming clusters. Clustering algorithms such as k-Means (Lloyd, 1982) or DBSCAN (Ester, M., Kriegel, H. P., Sander, J., & Xu, X., 1996) are used to group customers and articles. This improves the model's learning ability and data structure. Since the demand announcements, including past revised demand announcements, are in a generalized format and in this case include a large number of input dimensions, compression or convolution can improve training and data structure. This can be done on the feature extraction side by an autoencoder that learns a dimension-reduced latent representation of the input data (Hinton & Salakhutdinov, 2006). This representation contains almost the original information content and enables a reduction in model size and more efficient processing. Instead of dimension reduction at the data pre-processing level, convolutional layers can also be used at the network architecture level to enable efficient data propagation. As a reference, the convolutional networks are contrasted with pure feedforward networks. Another decisive aspect is the comprehensibility and explainability, which is crucial for acceptance and trust in the AI application (Afroogh et al., 2024). The probabilistic modeling of the output contributes to the interpretability and explainability of the model. In addition, architecture-independent model-agnostic methods such as SHAP can be used to increase transparency and interpretability. Furthermore, rule-based machine learning approaches with limited complexity can provide additional insight into traceability and explainability. Here, the advantages of traceability have to be evaluated against any losses in model quality. Although the processes of deliveries and orders represent recurring events that could be adequately modeled formally by recurrent neural networks (RNNs), specific requirements speak against the use of this architecture. A central aspect of the problem is the need to generate not only point predictions (quantities or points in time), but also probability distributions for future events. This is particularly crucial as decisions in procurement scheduling are typically made under uncertainty. In addition, the cumulative demand over a defined period of time is more relevant than isolated individual values, as this is directly linked to resource planning and allocation. However, the feedback of data within recurrent architectures poses considerable challenges.

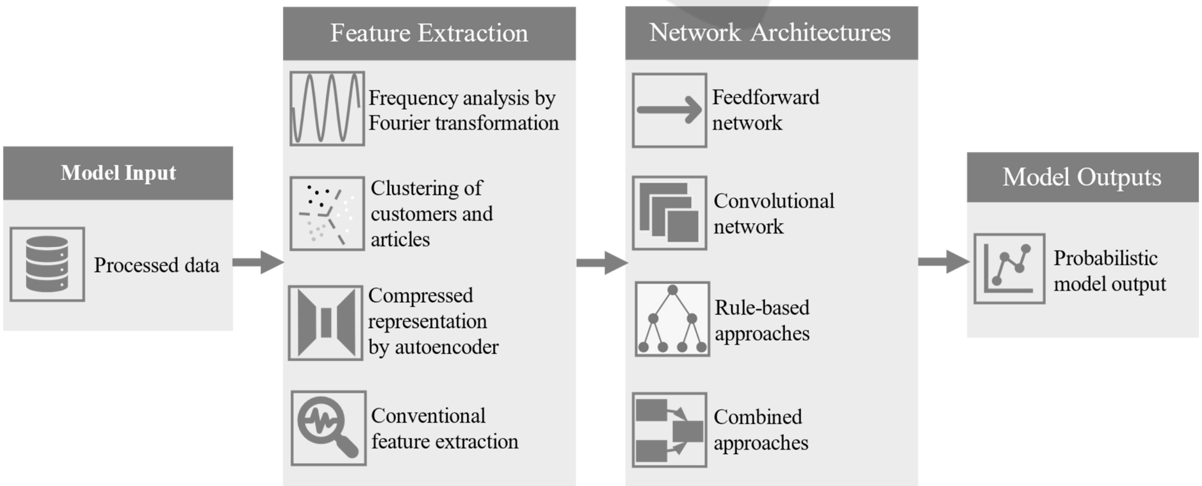

Figure 2: Design of experiment for machine learning algorithms.

In particular, either a large number of possible scenarios have to be modeled or probabilities cannot be adequately taken into account. These limitations would reduce the validity of the predictions and impair the practical applicability of the model. For this reason, approaches are preferred that can directly predict probabilities for future periods on the basis of historical data.

Model Output
Probabilistic modeling enables demand and procurement time to be expressed as a function of their probability of occurrence. This provides the basis for risk- or cash flow-optimized procurement scheduling and warehousing. A key advantage of this approach lies in the subsequent adjustment of the desired delivery reliability through user interaction. Quantifying the risk increases transparency and promotes acceptance and trust in the AI-based system (Magnus Liebherr et al., 2025). Modeling multiple output layers enables the simultaneous estimation of multiple target values. Typically, the loss functions to be minimized include the difference between the target variable and the prediction. The output can be calibrated to any quantile $q \in (0,1)$ by an asymmetric weighting of over- and underestimation:

$$L(y, \hat{y}) = \begin{cases} q\,(y-\hat{y}) & if\ y > \hat{y} \\ (1-q)(\hat{y}-y), & else \end{cases} \tag{1}$$

The choice of different weightings q in several output layers enables the simultaneous estimation of different quantiles or confidence intervals. By providing different confidence intervals and interpolation methods, the user can interactively explore risk-based scenarios and dynamically adapt scheduling parameters to changing framework conditions.

Aggregation of Probability Distributions
The AI-based model generates multivariate quantile forecasts for each customer-article pairing. The aggregated probability distributions of all customers per article are primarily relevant for decision-making in procurement scheduling. Depending on the number of customers and the granularity of the quantiles, these forecasts are calculated either analytically or empirically: an analytical convolution combines the individual distributions and calculates the resulting overall distribution with mathematical precision:

$$P_{total} = P_1 * P_2 * \dots * P_N \tag{2}$$

The convolution method is suitable due to the computational complexity with a lower number of customers and lower quantile granularity and provides a mathematically exact calculation. The Monte Carlo method approximates the resulting distribution empirically by sampling. The calculation effort can be reduced at the expense of accuracy. These methods are based on the assumption of stochastic independence between the probability distributions generated by the AI. In a global market, demand patterns can correlate due to common economic factors. If these factors are not fully integrated in the AI model, the premise of stochastic independence does not apply. The resulting systematic errors require an analysis that provides information about the demand correlation of different customers. Depending on the result of the analysis, the systematic errors can be compensated by integrating copula models, for example. If there is no significant correlation between certain customers, uncertainties can be compensated for by temperature scaling.

Probabilistic Calibration
Despite the use of regularization methods, machine learning algorithms have a tendency to overfitting, especially in more complex architectures (Sun et al., 2017). This overfitting leads to overconfident predictions for test or validation data. Temperature scaling offers an effective approach to improve calibration by introducing a scalar parameter T that scales the output distribution of the logits. Temperature scaling was originally developed for classification models (Chuan Guo et al., 2017). In 2020, Utpala & Rai show that the concept can also be applied to quantile calibrations in regression models (Utpala & Rai, 2020). The temperature parameter T is applied to the distribution function and can be estimated based on past data.

4 INITIAL RESULTS AND DISCUSSION

The process chain presented offers a generalized, AI-based approach to forecasting demand and procurement time. By integrating probabilistic modelling, the aggregation of individual customer demand at article level and temperature scaling, the system enables a realistic quantification of probabilities of occurrence and supports risk-adjusted and cash flow-optimized scheduling. Both human schedulers and downstream software agents can use the AI-supported forecasts to optimize decisions, increase delivery reliability and reduce storage costs. Explicit risk quantification increases the transparency of the system, thereby promoting user acceptance and building trust.

A first exemplary aggregated demand forecast over 52 weeks for a reference article (Figure 3) shows that the spread of the confidence intervals increases with increasing forecast horizon. In this case, the base model slightly underestimates demand, but the actual values are predominantly within the 90 % confidence interval (without applying temperature scaling).

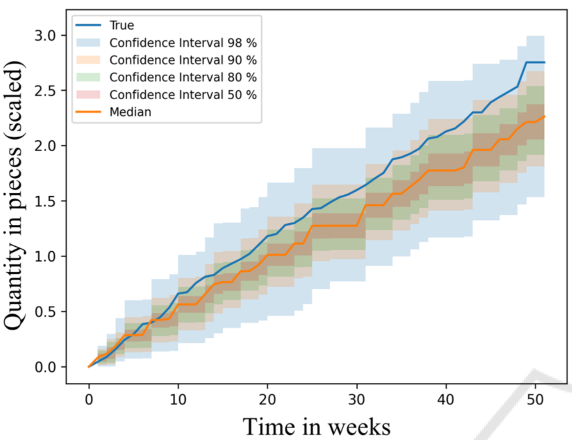

Figure 3: Exemplary aggregated demand forecast over 52 weeks.

The completion of the process chain includes a systematic analysis and optimization of model architectures and hyperparameters in order to further increase the prediction quality. Future work will address the adaptation of the process chain to the prediction of procurement times, the integration of explainable AI methods to increase traceability and the extension to correlated demand patterns in global supply chains using copula models. The presented AI-based process chain makes the central advantages of AI usable for SME in procurement scheduling by enabling risk-conscious, efficient and transparent scheduling, which both reduces storage costs and sustainably increases delivery reliability.

REFERENCES

Afroogh, S., Akbari, A., Malone, E., Kargar, M., & Alambeigi, H. (2024). Trust in AI: Progress, challenges, and future directions. *Humanities and Social Sciences Communications*, *11*(1), 1–30. https://doi.org/10.1057/s41599-024-04044-8

Allal-Chérif, O., Simón-Moya, V., & Ballester, A. C. C. (2021). Intelligent purchasing: How artificial intelligence can redefine the purchasing function. *Journal of Business Research*, *124*, 69–76. https://doi.org/10.1016/j.jbusres.2020.11.050

Amirkolaii, K. N., Baboli, A., Shahzad, M. K., & Tonadre, R. (2017). Demand Forecasting for Irregular Demands in Business Aircraft Spare Parts Supply Chains by using Artificial Intelligence (AI). *IFAC-PapersOnLine*, *50*(1), 15221–15226. https://doi.org/10.1016/j.ifacol.2017.08.2371

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

Bitkom e. V. (2022). *KI gilt in der deutschen Wirtschaft als Zukunftstechnologie – wird aber selten genutzt* [Retrieved March 29, 2025].

Business Forecast Systems, Inc. (2025). *forecast pro* [Retrieved April 26, 2025]. https://www.forecastpro.com/

Choung, H., David, P., & Ross, A. (2023). Trust in AI and Its Role in the Acceptance of AI Technologies. *International Journal of Human–Computer Interaction*, *39*(9), 1727–1739. https://doi.org/10.1080/10447318.2022.2050543

Chuan Guo, Geoff Pleiss, Yu Sun, & Kilian Q. Weinberger (2017). On Calibration of Modern Neural Networks. *International Conference on Machine Learning*, 1321–1330. http://proceedings.mlr.press/v70/guo17a.html

Chui, M., Hazan, E., Roberts, R., Singla, A., Kate, S., Sukharevsky, A., Yee, L., & Zemmel, R. (2023). *The economic potential of generative A* [Retrieved March 28, 2025]. https://www.mckinsey.com/~/media/mckinsey/business functions/mckinsey digital/our insights/the economic potential of generative ai the next productivity frontier/the-economic-potential-of-generative-ai-the-next-productivity-frontier

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

Ester, M., Kriegel, H. P., Sander, J., & Xu, X. (1996). *A density-based algorithm for discovering clusters in large spatial databases with noise*. Proceedings of the Second International Conference on Knowledge Discovery and Data Mining (KDD-96) (pp. 226-231). https://cdn.aaai.org/kdd/1996/kdd96-037.pdf?source=post_page---------------

Ferrario, A., & Loi, M. (2022). How Explainability Contributes to Trust in AI. In *2022 ACM Conference on Fairness, Accountability, and Transparency* (pp. 1457–1466). ACM. https://doi.org/10.1145/3531146.3533202

Hinton, G. E., & Salakhutdinov, R. R. (2006). Reducing the dimensionality of data with neural networks. *Science*, *313*(5786), 504–507. https://doi.org/10.1126/science.1127647

Lloyd, S. (1982). Least squares quantization in PCM. *IEEE Transactions on Information Theory*, *28*(2), 129–137. https://doi.org/10.1109/TIT.1982.1056489

Lundberg, S., & Lee, S.-I. (2017, May 22). *A Unified Approach to Interpreting Model Predictions*. http://arxiv.org/pdf/1705.07874

Lundborg, M., Papen, M.-C. Dr., Roloff, M., Simons, M. J., & Stamm, P. (2023). *Künstliche Intelligenz im Mittelstand* [Retrieved March 29, 2025]. https://www.mittelstand-digital.de/MD/Redaktion/DE/Publikationen/ki-Studie-2023.pdf?__blob=publicationFile&v=4

Magnus Liebherr, Ellen Enkel, Effie Law, Mohammadreza Mousavi, Matteo Sammartino, & Philipp Sieberg (2025). Dynamic Calibration of Trust and Trustworthiness in AI-Enabled Systems. *International Journal on Software Tools for Technology Transfer*. https://kclpure.kcl.ac.uk/portal/en/publications/dynamic-calibration-of-trust-and-trustworthiness-in-ai-enabled-sy

Manchon, J. B., Bueno, M., & Navarro, J. (2021). From manual to automated driving: How does trust evolve? *Theoretical Issues in Ergonomics Science*, *22*(5), 528–554. https://doi.org/10.1080/1463922X.2020.1830450

McKinsey & Company. (2021). *Succeeding in the AI supply-chain revolution* [Retrieved March 28, 2025]. https://www.mckinsey.com/industries/metals-and-mining/our-insights/succeeding-in-the-ai-supply-chain-revolution#/

OECD. (2023). *OECD SME and Entrepreneurship Outlook 2023*. Retrieved March 29, 2025. https://www.oecd.org/en/publications/oecd-sme-and-entrepreneurship-outlook-2023_342b8564-en.html, https://doi.org/10.1787/342b8564-en

Samuels, A. (2024). Examining the integration of artificial intelligence in supply chain management from Industry 4.0 to 6.0: A systematic literature review. *Frontiers in Artificial Intelligence*, *7*, 1477044. https://doi.org/10.3389/frai.2024.1477044

Shumway, R. H., & Stoffer, D. S. (2017). Arima Models. *Time Series Analysis and Its Applications*, 75–163. https://doi.org/10.1007/978-3-319-52452-8_3

Sun, X., Sun, W., Ma, S., Ren, X., Zhang, Y., Li, W., & Wang, H. (2017, November 25). *Complex Structure Leads to Overfitting: A Structure Regularization Decoding Method for Natural Language Processing*. http://arxiv.org/pdf/1711.10331

Taylor, S. J., & Letham, B. (2018). Forecasting at Scale. *The American Statistician*, *72*(1), 37–45. https://doi.org/10.1080/00031305.2017.1380080

Utpala, S., & Rai, P. (2020). *Quantile Regularization: Towards Implicit Calibration of Regression Models.*

Venkatesan, S. P., & Goh, M. (2016). Multi-objective supplier selection and order allocation under disruption risk. *Transportation Research Part E: Logistics and Transportation Review*, *95*, 124–142. https://doi.org/10.1016/j.tre.2016.09.005

WIK GmbH (Ed.). (2019). *https://www.mittelstand-digital.de/MD/Redaktion/DE/Publikationen/kuenstliche-intelligenz-im-mittelstand.pdf?__blob=publicationFile&v=5* [retrieved March 28, 2025]. Begleitforschung Mittelstand-Digital.

Wong, L.-W., Tan, G. W.-H., Ooi, K.-B., Lin, B., & Dwivedi, Y. K. (2024). Artificial intelligence-driven risk management for enhancing supply chain agility: A deep-learning-based dual-stage PLS-SEM-ANN analysis. *International Journal of Production Research*, *62*(15), 5535–5555. https://doi.org/10.1080/00207543.2022.2063089