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Artificial Intelligence in the German Chemical and Pharmaceutical Industry: A Comparative Analysis of Empirical Survey Results from 2020 and 2025

Anke Dassler, Evgenia I. Lysova, Svetlana N. Khapova, Konstantin Korotov
Employer attractiveness in the Chemical Industry: Investigating the impact of product novelty, product relevance, and work meaningfulness

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Sustainable Use of PiWi Vine Leaves: Life Cycle Assessment and Techno-Economic Analysis of a Novel Vine-Leaf-Based Beverage within the Framework of the Circular Bioeconomy

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Editorial Board

Aim and Scope

The Journal of Business Chemistry (JoBC) focuses on current developments and insights at the intersection of management and chemistry, biotechnology or pharmacy.

The JoBC provides an international forum for researchers and practitioners in companies, research institutes, public authorities, consultancies or NGOs to present and discuss current challenges as well as potential solutions in an interdisciplinary manner. Thus, the JoBC aims to foster the dialog between science and business, to support management practice in the chemical and pharmaceutical industry and to indicate where further research from academia is needed. The JoBC offers high quality publications with academic standards, a fast publishing process and global reach. With this multidisciplinary and boundary-spanning approach, the JoBC intends to become the leading journal for decision makers in the chemical and pharmaceutical industry.

Publisher

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Letter from the Editors

Transforming Industries Responsibly: Digitalization, Meaning, and Circular Innovation

As 2025 draws to a close, we witness a period of profound transformation across the chemical and pharmaceutical industries. Digitalization and artificial intelligence have evolved from emerging trends into defining elements of industrial competitiveness and organizational identity. At the same time, the search for purpose, sustainability, and responsible innovation continues to guide corporate strategy. This final issue of the Journal of Business Chemistry for 2025 reflects these dynamics - capturing how technology, meaning, and circularity jointly shape the future of business chemistry.

We are honored to introduce ourselves as the new editors of the Journal of Business Chemistry: Sabrina Duswald and Friederike Fontes. We sincerely thank the former editorial team for their many years of commitment and for their contributions to establishing the Journal of Business Chemistry as a respected platform for research and practice alike. Building on the strong foundation established by our predecessors, we aim to continue the journal's mission of bridging the gap between management and the natural sciences. Our shared goal is to further strengthen the journal's international orientation and to encourage interdisciplinary dialogue on innovation, sustainability, and responsible business transformation within the chemical, pharmaceutical, and biotechnological sectors. As the industries we study evolve, so does our mission: to highlight how new technologies and business models can drive competitiveness without compromising ethical or environmental responsibility.

We open this issue with the article "Artificial Intelligence in the German Chemical and Pharmaceutical Industry: A Comparative Analysis of Empirical Survey Results from 2020 and 2025" by Thorsten Daubenfeld, Fé Hasselbach and Svenja Just. Drawing on a longitudinal survey, the authors reveal how the adoption of artificial intelligence has expanded dramatically within five years - from selective experimentation to broad, multi-functional application. Their findings highlight not only the speed of digital transformation but also the new organizational and technical challenges that accompany it.

Next, Anke Dassler, Evgenia I. Lysova, Svetlana N. Khapova and Konstantin Korotov investigate the human dimension of innovation in "Employer attractiveness in the chemical industry: Investigating the impact of product novelty, product relevance and work meaningfulness." Their study shows that internal employer attractiveness is shaped not only by HR instruments but also by how employees perceive the novelty and societal value of their company's products. The work underscores the importance of purpose and meaning in retaining skilled talent within highly innovative environments.

Finally, Marie Sauer and Ralf Ehret bridge the gap between sustainability assessment and product innovation in "Sustainable Use of PiWi Vine Leaves: Life Cycle Assessment and Techno-Economic Analysis of a Novel Vine-Leaf-Based Beverage within the Framework of the Circular Bioeconomy." By combining life cycle and techno-economic analysis, the authors illustrate how circular bioeconomy concepts can generate both ecological and economic value through the upcycling of agricultural by-products. Together, these contributions capture the breadth of transformation shaping today's industries - from digital intelligence to human motivation and ecological regeneration. They demonstrate that sustainable progress depends on integrating innovation with responsibility, and technology with purpose.

Please enjoy reading the third issue of our journal in 2025. If you have any comments or suggestions, feel free to contact us at contact@businesschemistry.org. For ongoing updates and insights, follow us on LinkedIn: www.linkedin.com/company/jobc and subscribe to our newsletter.

We extend our heartfelt thank you to all authors, reviewers, and readers for their engagement and support throughout the year.

Warm regards,

Friederike Fontes (née Woltmann)
(Executive Editor)

Sabrina Duswald
(Executive Editor)

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Research Paper

Thorsten Daubenfeld*, Fé Hasselbach, Svenja Just

Artificial Intelligence in the German Chemical and Pharmaceutical Industry: A Comparative Analysis of Empirical Survey Results

This study presents a comparative analysis of survey data collected from 124 companies in the German chemical and pharmaceutical industry in 2020 and 2025. The findings reveal a clear upward trend in digitalization: in 2025, 91% of companies rated digitalization as "relevant" or "very relevant", up from 75% in 2020. Over this period, digital initiatives shifted from a focus on basic IT infrastructure and communication tools to a more consistent integration of artificial intelligence (AI). The adoption of AI grew substantially, with active use expanding from 34% of companies in 2020 to 76% in 2025. Generative AI tools, such as ChatGPT and customized enterprise assistants, are increasingly embedded in daily operations, particularly in large firms and a rising number of SMEs. AI's relevance is highest in research & development and customer service, likely reflecting new generative AI capabilities. Main obstacles to AI shifted from organizational and budget issues in 2020 to technical and regulatory challenges, particularly IT security, in 2025. Mid-sized companies (50-999 employees) report the greatest difficulties in keeping pace with digital transformation. Overall, the sector is transitioning from isolated pilot projects to broad, multi-functional use of AI technologies.

Introduction

The chemical and pharmaceutical industries are undergoing rapid digital transformation, driven by advances in automation, data analytics, and increasingly, artificial intelligence (AI). AI applications have moved beyond niche uses in process optimization and forecasting to become integral tools in day-to-day business operations. The broad potential of AI in these sectors is well established (Henstock, 2019; Baum, 2021; Mowbray, 2022; Womack, 2022; Laska, 2023; Toniato, 2023; Konrad, 2024; Ananikov, 2024). Key areas of application include research and development (Ulbrich, 2021; Womack, 2020; Laska, 2023; Konrad, 2024), drug development (Mak, 2018; Kulkov, 2021; Patel, 2022; Vora, 2023; Maharjan, 2023), production (Womack, 2020; Kulkov, 2021; Chiang, 2022; Laska, 2023; Maharjan, 2023; Konrad, 2024), supply chain management (Womack, 2020; Kulkov, 2021; Chiang, 2022; Laska, 2023; Konrad, 2024), sales and customer service (Womack, 2020; Kulkov, 2021; Konrad, 2024), regulatory affairs (Walsh, 2021), sustainable chemistry (Toniato, 2023), quality assurance (Kulkov, 2021; Laska, 2023), and innovation in start-ups (Dreiling, 2025). Despite extensive documentation of AI's relevance, comprehensive research on its actual implementation and changing significance over time remains limited. Existing studies include a global survey of 400 executives in the

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chemical industry (Womack, 2020), qualitative interviews with executives in pharmaceutical firms (Kulkov, 2021), and sector-specific reviews (Chiang, 2022; Patel, 2022). However, there is no systematic analysis focusing on the German chemical and pharmaceutical industry.

This study addresses this gap by presenting and comparing survey results from German chemical and pharmaceutical companies in 2020 and 2025. The analysis covers company demographics, digitalization strategies, adopted measures, AI uptake and understanding, and perceived barriers to implementation. By examining changes over time, the study offers new insights into evolving trends and challenges in digitalization and AI adoption within these sectors.

2 Methods

This study uses a mixed-methods design, combining quantitative and qualitative survey approaches to assess the development of digitalization and artificial intelligence (AI) in the German chemical and pharmaceutical industry. Data were collected via standardized online questionnaires, distributed to industry professionals in two survey waves, in 2020 and 2025.

2.1 Survey Design

The questionnaires covered three core areas: (1) company and respondent demographics (industry sector, role, and employee count), (2) digitalization practices and obstacles, and (3) AI understanding, usage, and obstacles. Both closed-ended (single-choice and Likert-scale) and open-ended questions were used to ensure data depth and comparability. Closed questions assessed topic relevance and obstacles, while open questions captured detailed experiences and perspectives on digitalization and AI. Company size was benchmarked against the categories defined by the German Chemical Industry Association (VCI) to assess sample representativeness.

2.2 Sampling and Data Collection

Respondents included employees from companies of various sizes, roles, and functions within the chemical and pharmaceutical sectors. Recruitment took place through professional and alumni networks, email invitations, and LinkedIn outreach, targeting both SMEs and large enterprises. Participation was voluntary and all responses were anonymized.

2.3 Data Processing and Analysis

Closed-ended responses were analyzed quantitatively using descriptive statistics and visualized with bar charts. Open-ended answers were grouped into thematic categories. Results from the two survey waves were compared side by side to identify trends and changes over time. This comparative approach enabled analysis of key developments and ongoing challenges in digitalization and AI within the industry.

3 Results

3.1 Sample Characteristics

In the 2020 survey, 68 questionnaires were returned, with 66 completed and included in the analysis. In 2025, 81 questionnaires were returned, 57 of which were complete and analyzed. The total number of companies in the sector was 4,013 in 2020 (VCI 2022) and is currently (latest data refer to 2023) around 2,000 (VCI 2024). Given the small survey sample compared to the industry total, results should be viewed as exploratory rather than representative.

We compared the distribution of survey respondents to VCI employee size classes (Fig. 1). Both surveys included companies of varying sizes. In 2020, respondents from the 50-249 and 1000+ employee segments were proportionally similar to the sector average, but those from <50 employees were overrepresented and those from 250-999 employees underrepresented, potentially biasing results toward smaller and larger companies.

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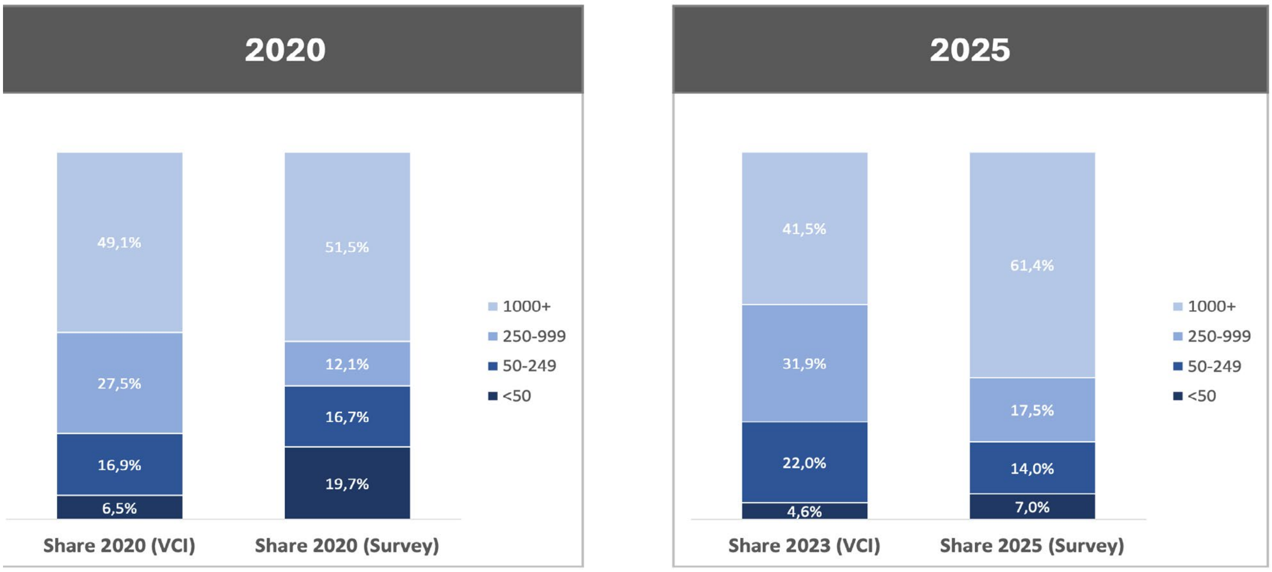

Figure 1 Comparison of the distribution of survey respondents by company size (number of employees) in 2020 (left, N=66) and 2025 (right, N=57) with the overall industry distribution according to VCI classification.

In the 2025 survey, respondents from companies with 1000+ employees were overrepresented compared to the industry average, while the share from <50 employees was closer to industry proportions. Respondents from the 50-249 and 250-999 employee categories were underrepresented, though still sufficient for analysis. This distribution (see Fig. 1) should be considered when interpreting results, as it may introduce bias.

Regarding industry sectors, both surveys showed similar distributions (Fig. 2). Most respondents work in chemical and pharmaceutical companies, including sectors such as distribution and biotechnology/diagnostics. Other mentioned sectors include plant engineering, consumer goods, coatings, contract research, manufacturers/suppliers of additives/auxiliaries, analytical service providers, and consulting.

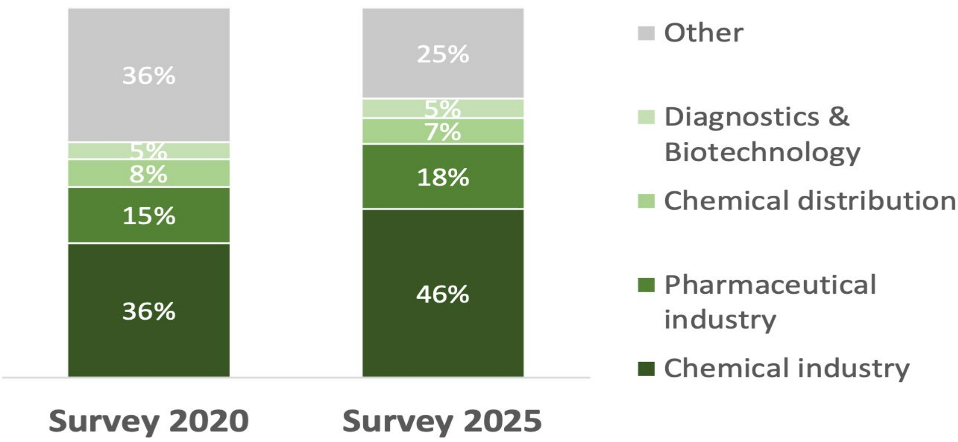

Figure 2 Distribution of survey respondents by industry sector in 2020 (N=66) and 2025 (N=57).

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Since most respondents work in the targeted industry sectors, the survey results for this category are considered valid for addressing the research question.

A similar pattern is seen in the organizational positions of respondents in both surveys (Fig. 3). Most work in R&D, reflecting its importance in the chemical and pharmaceutical industry. Around 14–15% are in Marketing and Sales, often covering technical sales and service in B2B. Other relevant functions represented include management, Quality Management (QM), and Production, covering key stages of the value chain. The "Other" category includes roles such as Procurement/Purchasing, Business Development, Supply Chain, Digitalization, Project Management, Product Stewardship, and Application Engineering.

The respondents' positions in both surveys are both comparable and relevant to our research question.

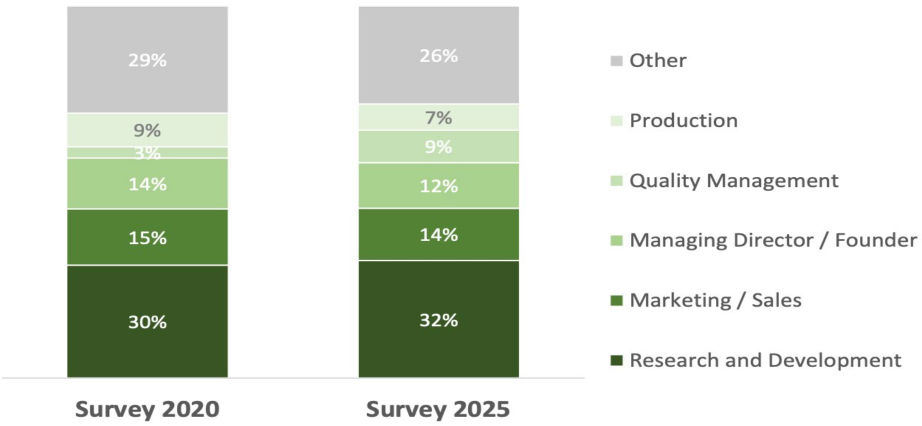

Figure 3 Distribution of survey respondents by organizational position in 2020 (N=66) and 2025 (N=57).

3.2 Digitalization in the Chemical and Pharmaceutical Industry

Digitalization is a prerequisite for AI. Therefore, we first surveyed the status of digitalization in the chemical and pharmaceutical industries. Figure 4 shows responses to the question: „How relevant is digitalization in your company?"

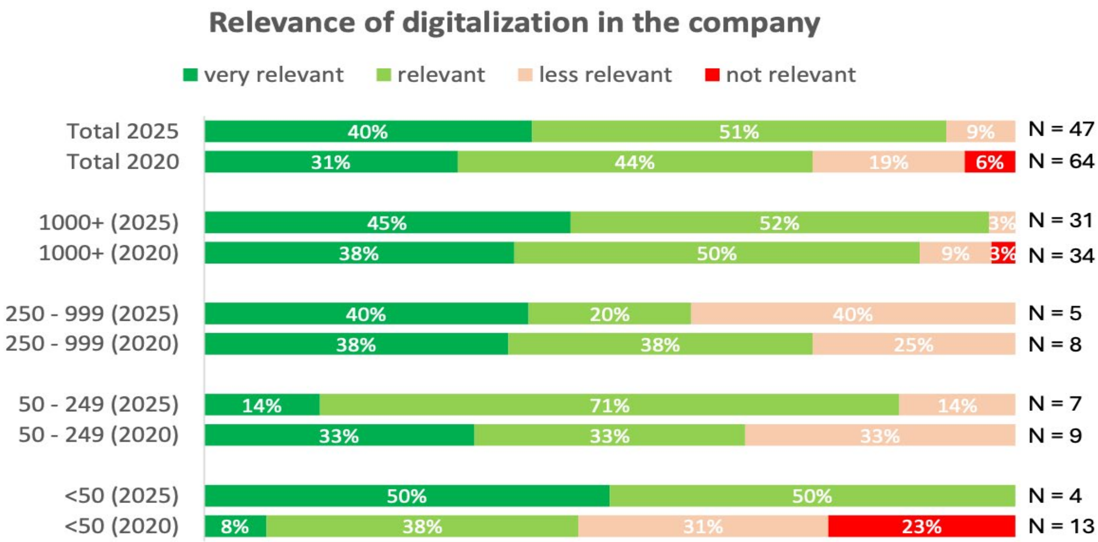

Figure 4 Relevance of digitalization in the 2020 and 2025 surveys. Total numbers and breakdown by company size.

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The results show that digitalization was already highly relevant in 2020, and its relevance has increased since then. This reflects a clear awareness of digitalization's importance and suggests that the digital competence of companies has grown. This trend may have been accelerated by the Covid-19 pandemic – the 2020 survey (February-June 2020) took place during the first lockdown – as well as the introduction of large language models (LLMs) since 2022.

Breaking down these findings by company size provides further detail (Fig. 4, lower part). The increased importance of digitalization was observed across all size categories, with the exception of companies with 250-999 employees, where there was a slight decrease. In the 2025 survey, digitalization was not rated as „not relevant" by any respondent, which highlights its growing significance.

The relevance of digitalization has especially increased in small companies (<50 employees) and large corporations (1000+ employees). For companies with 50-999 employees, digitalization is somewhat less prominent but remains important. While digitalization's importance decreased with smaller company size in 2020, the results from 2025 present a more nuanced picture. Nonetheless, it aligns with studies showing that SMEs are generally less advanced in digitalization than larger companies (Fraunhofer ISI and IW Consult, 2024), although those studies were not focused specifically on the chemical and pharmaceutical industry.

Analysis of open-ended responses to „What concrete measures related to digitalization have already been implemented in your company?" provided further insight (Tab. 1). The data in Table 1 should be interpreted carefully, since categorizing open-ended responses relies on subjective judgment. However, this overview offers an indication of the relevance of individual topics.

Table 1 Classification of open-ended responses to the question "What concrete measures related to digitalization have already been implemented in your company?".

Category	*Number of answers in Survey 2020*	*Exemplary Answers from Survey 2020*	*Number of Answers in Survey 2025*	*Exemplary Answers from Survey 2025*
Organization & Strategy	1 (0.9%)	„Establishment of a digitalization group in production with a strategic budget and harmonization mandate"	7 (8.0%)	"The position of Chief Digitalisation Officer was established" "Integration of digitalization goals into the target agreements of each employee"
IT Systems & Infrastructure	18 (17.0%)	„Introducing Office 365 and working with Teams" „Implementation of SAP"	12 (13.8%)	"Own IT team with extensive programming skills, programming own programs to meet individual requirements" "SAP S4/Hana as a central ERP with connection/integration of all processes in the company" "Introduction of MES" "Consolidation of digital tools"
Data Management & Analytics	14 (13.2%)	"Establishment of a central data warehouse" "Introduction of a data lake for individual departments" "Key Word search in laboratory journals"	9 (10.3%)	"Database completely in the cloud" "Consolidation of the many Excel digital laboratory journals worldwide" "Access to current and historical information on production data, quality data and their visualization"

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Category	*Number of answers in Survey 2020*	*Exemplary Answers from Survey 2020*	*Number of Answers in Survey 2025*	*Exemplary Answers from Survey 2025*
Process Digitization & Automation	20 (18.9%)	"Paperless office (partially)" "Automation of simple processes" "Conversion from ‚manual' processes, e.g. in accounting or in production/quality management, to digital processes"	19 (21.8%)	"Digitization of signatures and document filing, administrative processes for invoice processing and contract management" "Digitization of all documents relevant to the employee (e.g. digital proof of earnings)" "Digitalization has been completely implemented" "The company is completely digital. Docusign, cloud storage, all MS tools, and proprietary AI solutions. Everything is in place."
Communication & Collaboration	19 (17.9%)	"Introducing Office 365 and working with Teams" "Elimination of telephones, purchase of tablets (also for use in the laboratory), most training courses are conducted via an online training portal, etc." "Digital communication platform for all employees (even those without an email address)" "All employees can work from home independently of other infrastructure"	9 (10.3%)	"Conversion of employee working methods to Office365" "Use of online meetings and thus mobile working" "Investment in high-quality home office equipment for employees to work remotely"

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Category	*Number of answers in Survey 2020*	*Exemplary Answers from Survey 2020*	*Number of Answers in Survey 2025*	*Exemplary Answers from Survey 2025*
Customer Management, Sales & Marketing	14 (13.2%)	"Data integration in the supply chain from ordering through production and storage to delivery to the customer and the payment process" "Introduction of CRM system" "Standardization of the ordering and sales system" "Introduction of a large-scale customer relationship management system to better manage the large number of customers and obtain data from customer behavior."	5 (5.7%)	"Digital sales team, digitalization of order management through appropriate tools in the customer service area" "Big Commerce Webshop, Digital Marketing and Augmented Reality based Service support"
Production Digitization & Smart Manufacturing	11 (10.4%)	"(Higher) automation of production facilities, e.g.,augmented reality', ,predictive maintenance' "Partial digitalization of production facilities"" "Smart production facilities" "Introduction of augmented reality in production" "Direct interface between CRM and production planning"	6 (6.9%)	"Use of autonomous vehicles for freight transport" "Machine connection, MES deployment" "
AI, Innovation & Research	3 (2.8%)	„Use of AI to analyze complex data sets (texts, numbers)"	17 (19.5%)	"Implementation of an in-house AI chatbot" "Use of AI in the research and development of new drugs" "Development of your own AI tool or modification for various applications (sales, research, operations, etc.)" "Development and implementation of own AI solutions"
Other / No Measures	6 (5.7%)	„When it comes to digitalization, we are still at the very beginning"	3 (3.4%)	„Virtually none. The digitization of reports is not well thought out, and AI is used as a toy."

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In 2020, most digitalization measures taken by companies focused on establishing IT infrastructure, improving internal and external communication, process and production automation, and data analytics. This is not surprising, given the chemical and pharmaceutical industries' traditional focus on process optimization, which makes digitalization in production and automation a logical step. The emphasis on communication can also be attributed to the timing of the survey, conducted during the first Covid-19 lockdown, when virtual communication – both internally (among employees) and externally (with suppliers and customers) – became essential.

The landscape changed in 2025. While IT systems and infrastructure, data management and analytics, and process digitization/automation remained important, communication was mentioned less frequently than in 2020. This likely reflects the normalization of virtual communication and reduced necessity compared to the lockdown period. Notably, "AI, Innovation & Research" emerged as one of the most prominent topics in 2025, whereas it was only sporadically mentioned in 2020. This is particularly striking because the questionnaire did not explicitly prompt respondents to discuss AI.

When respondents rated predefined digitalization topics, an increase was observed across all areas (Fig. 5).

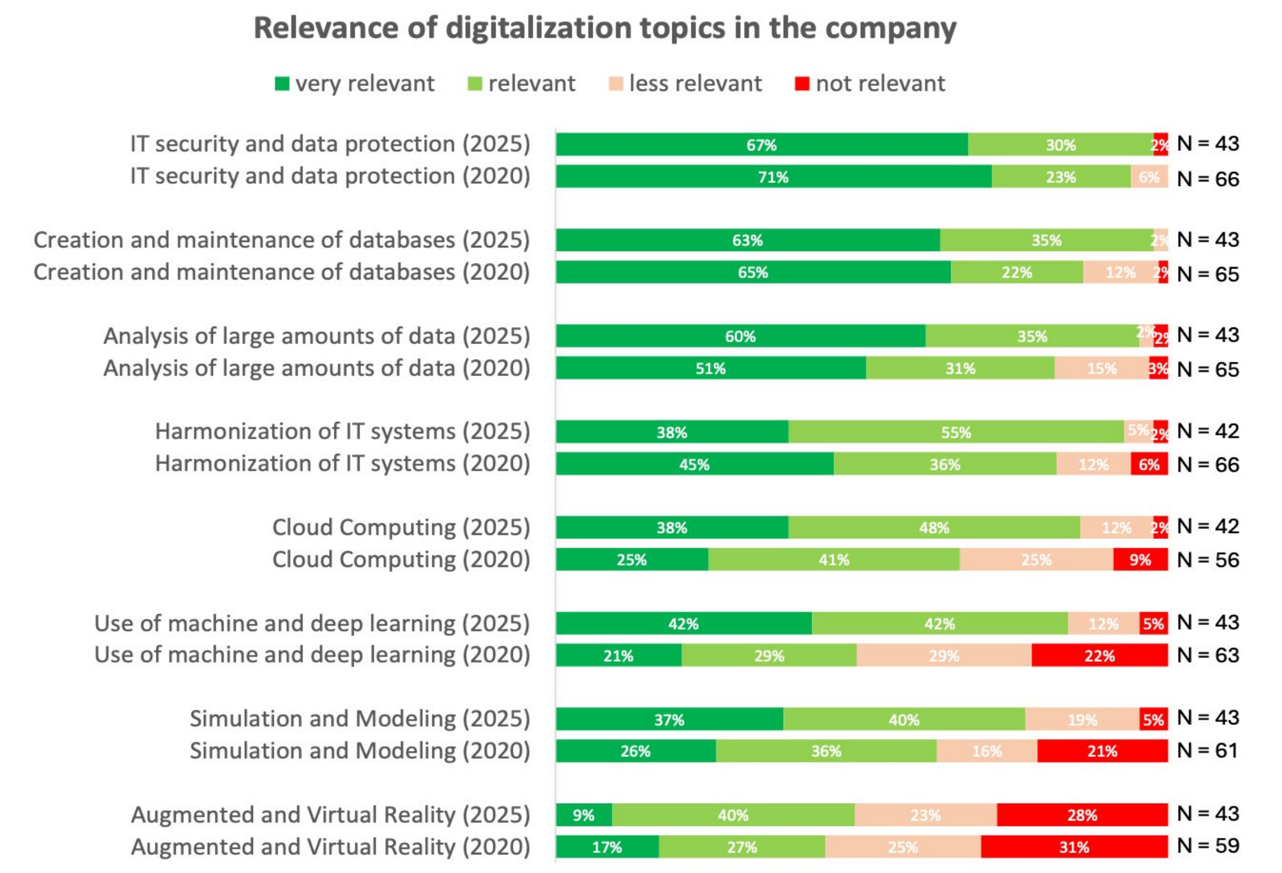

Figure 5 Assessment of relevance of digitalization topics in the 2020 and 2025 surveys.

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All specified topics were rated at least moderately relevant – at least 40% of respondents assessed them as "very relevant" or "relevant" – and most topics reached high relevance, with over 70% of respondents giving these ratings in the chemical and pharmaceutical industries. Importantly, all topics have become more relevant since 2020 (dark green and green bars in Fig. 6). IT security and data protection ranked highest in relevance, likely reflecting the impact of European legislation such as the GDPR (DSGVO), in effect since 2018.

Topics directly or indirectly related to analytical AI also increased substantially in relevance. This is most notable in the rising importance of machine and deep learning between 2020 and 2025. These technologies require large data volumes stored in databases – on local servers or in the cloud – which is reflected in the growing relevance of these topics. The increased relevance of harmonizing IT systems, a prerequisite for efficiently creating company-wide data lakes, is consistent with these trends.

Augmented and virtual reality were rated least relevant overall but held greater importance in large companies (1,000+ employees), with about 60% rating them as "very relevant" or "relevant" in 2020 and 80% in 2025; however, SMEs saw these topics as less important. Further research is needed to better understand this observation.

The obstacles to digitalization in chemical and pharmaceutical companies are similar in both 2020 and 2025 (data not shown; details are provided in the supplementary materials). The main challenge continues to be the complex change process associated with digitalization. This includes (a) a lack of mindset, where employees may not recognize the necessity for change, (b) a lack of strategy and coordination, suggesting that management does not always provide clear direction, and (c) a complex change process, even once the need for change is acknowledged by both employees and management. Additional obstacles identified include limited budgets and resources, as well as insufficient skills to facilitate and support the change process.

The complexity of the IT landscape is also frequently mentioned as a major obstacle. Harmonizing IT systems proves difficult, especially when companies use a variety of incompatible systems for functions such as accounting, HR, and CRM.

When comparing the survey results from 2020 and 2025, it appears that implementation-oriented obstacles – such as lack of skills and the complexity of the change process – have become more significant, while foundational issues like lack of mindset and limited budgets or resources are less prominent. This may indicate that companies in the chemical and pharmaceutical industries are progressing towards the practical implementation of digitalization and are moving beyond preliminary debates.

3.3 Artificial Intelligence in the Chemical and Pharmaceutical Industry

Before exploring the use of AI in chemical and pharmaceutical companies, survey participants were asked, "What do you understand by artificial intelligence (AI)?" This question aimed to assess whether respondents had a thorough understanding of the topic or only a superficial view. The results are presented in Table 2.

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Table 2 Classification of open-ended responses to the question "What do you understand by artificial intelligence (AI)?".

Category	*Number of answers in Survey 2020*	*Exemplary Answers from Survey 2020*	*Number of Answers in Survey 2025*	*Exemplary Answers from Survey 2025*
Data analysis, Pattern recognition & prediction	15 (26.3%)	"An algorithm that can learn from known data and use it to create a forecast for the future" "A method for evaluating large amounts of data (analytics)" "Predicting product quality using process parameters"	9 (25.0%)	"A technology that is capable of processing large amounts of information (including graphic information) from a wide variety of sources and preparing it according to human requirements in order to then use it further itself or make it usable by humans" "The ability to use large amounts of data with the help of models and large computing capacity to predict/model new facts"
Process Control & Decision Support	16 (28.1%)	"Software learns the behavior of the person operating it and automates processes in the future without the intervention of an operator" "That a system with unpredictable situations, without intervention of a third party, independently assesses a situation and adapts its approach so that the task implemented in the system is completed as specified" "IT systems that help evaluate data and support users in making decisions or make them alone"	3 (8.3%)	"Beyond the mere evaluation of large amounts of data, decisions can also be formulated" "Decision support through machine learning, suggestions for decision making"
Creation of new content	0 (0.0%)		4 (11.1%)	"A very large database that can independently solve problems and produce its own content based on the stored data" "Independent reaction to a defined input (text, components, data)"
Replicating Human Intelligence	8 (14.0%)	"Automation and replication of intelligent behavior" "The attempt to transfer human behavior (especially learning, thinking, reasoning) to ‚machines' "Introduction of human-like machines"	7 (19.4%)	"Machines that can imitate human thinking" "Human-like abilities such as learning, problem-solving and decision-making through algorithms and data processing" "By AI I understand the ability of machines (software) to show human-like intelligence"

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Category	Number of answers in Survey 2020	Exemplary Answers from Survey 2020	Number of Answers in Survey 2025	Exemplary Answers from Survey 2025
Self-learning and evolving systems	9 (15.8%)	"Programming that can do more than what it's been taught. A self-learning system." "A computer that has the ability to expand its knowledge and skills through learning." "Programs that work independently and learn and develop from the work carried out"	2 (5.6%)	„A system that can not only execute learned processes/tasks, but can also develop further through independent learning"
Tool / Software	3 (5.3%)	„Support of ongoing work through automatic digital evaluations and rapid dissemination of information to all employees who need it"	6 (16.7%)	"LLM like ChatGPT" "Quick help with some topics"
Unclear / Wrong	4 (7.0%)	"Robot" "For me, AI is an industry buzzword used by people who cannot better describe the nature of the algorithm they use"	4 (11.1%)	"A very large database that is ‚fed' with information by people" "The automated processing of data using the knowledge of the WWW"
Other	2 (3.5%)	„There is no such thing as artificial intelligence. There are algorithms that, through intensive ‚learning', can sometimes solve certain tasks better than a human."	1 (2.8%)	„I usually use the external definitions rather than coming up with my own"

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It is evident that most survey participants had a well-informed and nuanced understanding of AI in both the 2020 and 2025 surveys. The most prominent responses in 2020 related to key areas of AI application, such as "Data analysis, Pattern recognition & prediction" and "Process Control & Decision Support." While data analysis remained the leading answer in 2025, process control and decision support were mentioned less frequently. Notably, the category "Creation of new content" appeared only in the 2025 survey, likely due to the growing presence of generative AI, such as LLM-based systems. Similarly, a larger proportion of responses in 2025 focused on specific software or tools, reflecting greater familiarity and hands-on experience with AI, as generative tools have become more widely used both professionally and privately.

The category "Self-learning and evolving systems," though not an incorrect definition, is rather vague, and its relative importance declined from 2020 to 2025 as AI became more mainstream. However, some unclear or incorrect notions of AI persist, as indicated by this category in both surveys. Overall, the answers confirm that survey participants generally have a sound understanding of AI, which supports the validity of the study's results.

When asked whether AI is used in their company, participants reported a clear shift towards more intensive AI adoption in 2025 compared to 2020 (see Fig. 6).

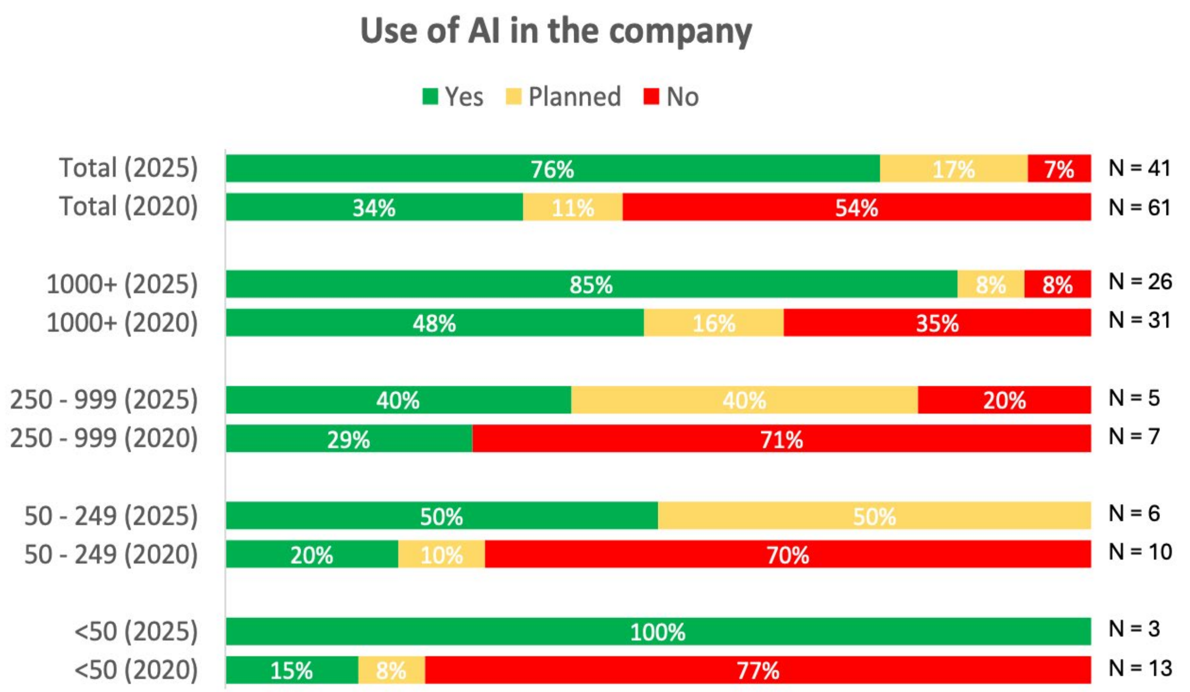

Figure 6 Visualization of results to the question "Is AI used in your company?", 2020 and 2025. Total numbers and breakdown by company size.

In 2025, most companies either already use AI or plan to do so in the future. This marks a stark contrast to 2020, when only about one third of companies had implemented AI and more than half of survey participants indicated that AI usage was not even planned within their organizations. While some bias cannot be ruled out – such as different awareness levels among respondents depending on their position (e.g., an R&D employee may not know of management-level AI initiatives) – the significant increase in positive responses in 2025 compared to 2020 demonstrates that AI has firmly established itself in the chemical industry.

This upward trend in AI adoption since 2020 is reflected across different company sizes, although the situation is more nuanced. AI uptake is particularly high among large companies (1,000+ employees) and small companies (<50 employees), while companies in the 50-999 employee range appear to lag behind in terms of actual implementation.

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Despite their plans to use AI in the future, these mid-sized companies have not adopted AI to the same extent yet.

Survey participants were then asked, “How exactly is AI used in your company?” (data not shown; details are provided in the supplementary materials). In 2020, AI initiatives were primarily limited to individual pilot projects or focused on automating repetitive tasks, especially in the areas of data analysis and forecasting. Some applications in research and development were also mentioned. By 2025, the landscape had evolved significantly: generative AI became a major driver of adoption within chemical and pharmaceutical companies. Solutions such as ChatGPT, Copilot, company-specific GPTs, assistants, and chatbots were either firmly integrated into daily operations or actively tested and implemented. Alongside its “traditional” role in data analysis, AI is now increasingly regarded as a tool for supporting work and expanding communication – for example, in marketing.

We complemented this analysis by asking, “How relevant is the use of AI along the value chain in your company?” and specifying individual steps within the corporate value chain. The results are presented in Figure 7.

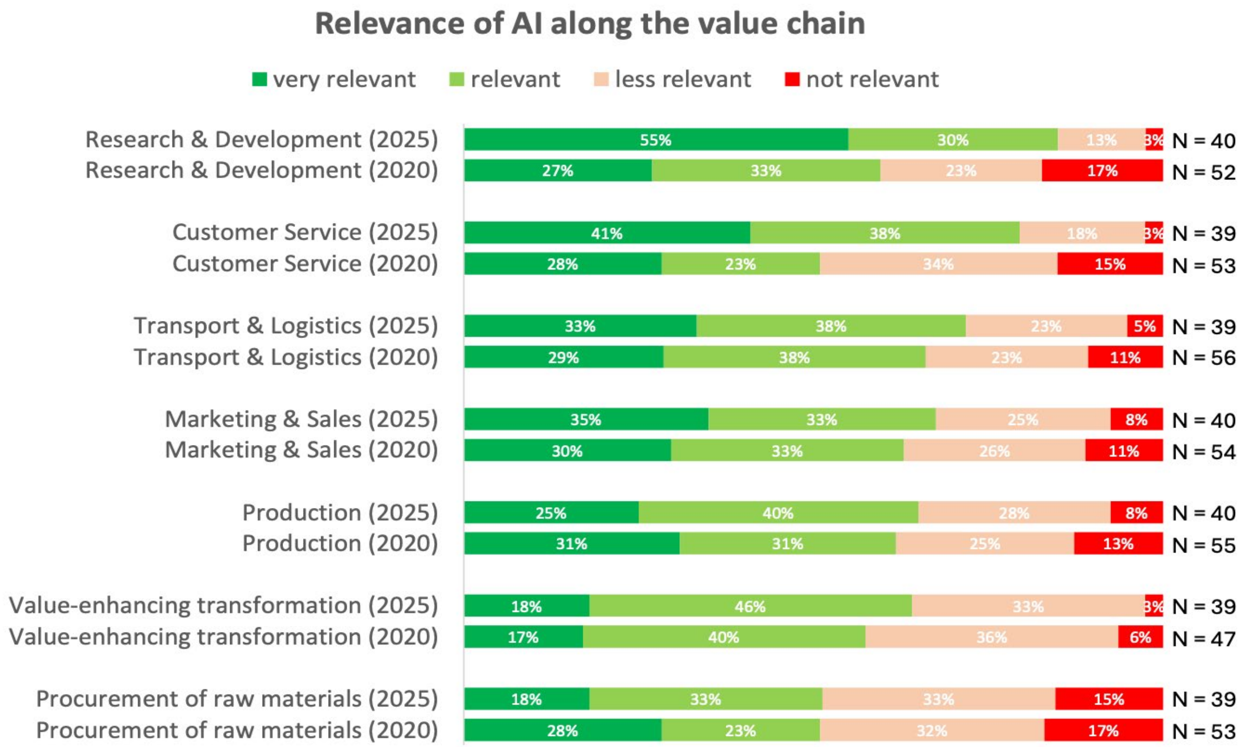

Figure 7 Visualization of results to the question “How relevant is the use of AI along the value chain in your company?”, 2020 and 2025.

It is evident that AI is relevant to all the mentioned steps in the value chain, with at least 50% of survey participants in both 2020 and 2025 rating all steps as “very relevant” or “relevant.” The greatest increase in relevance was observed in Research & Development (+25 percentage points for “very relevant” or “relevant”) and Customer Service (+29 percentage points). These two areas are where generative AI is expected to have the highest impact, which also aligns well with the results shown in Table 4. For all other value chain steps, there is a slight overall increase in the importance of AI, although the 2025 results are similar to those from 2020. This may be explained by the fact that most of these steps are related to the direct material flow within the company and are thus more closely tied to the production process. In these areas, analytical AI is expected to play a larger role than generative AI. It is likely that analytical AI was already widely adopted in the chemical and pharmaceutical industry by 2020, which could explain the lack of major

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developments in these areas over the last five years.

We then asked survey participants, based on the current use of AI, “How relevant are the AI topics listed below for your company now compared to the future?” The topics included a range of AI-related areas such as “predictive analytics,” “intelligent automation,” and “knowledge management.”

In the survey, “future” referred to the year 2025 for the 2020 survey and the year 2030 for the 2025 survey, which enabled us to compare the 2020 forecast with the actual results from the 2025 survey. The results are shown in Figure 8.

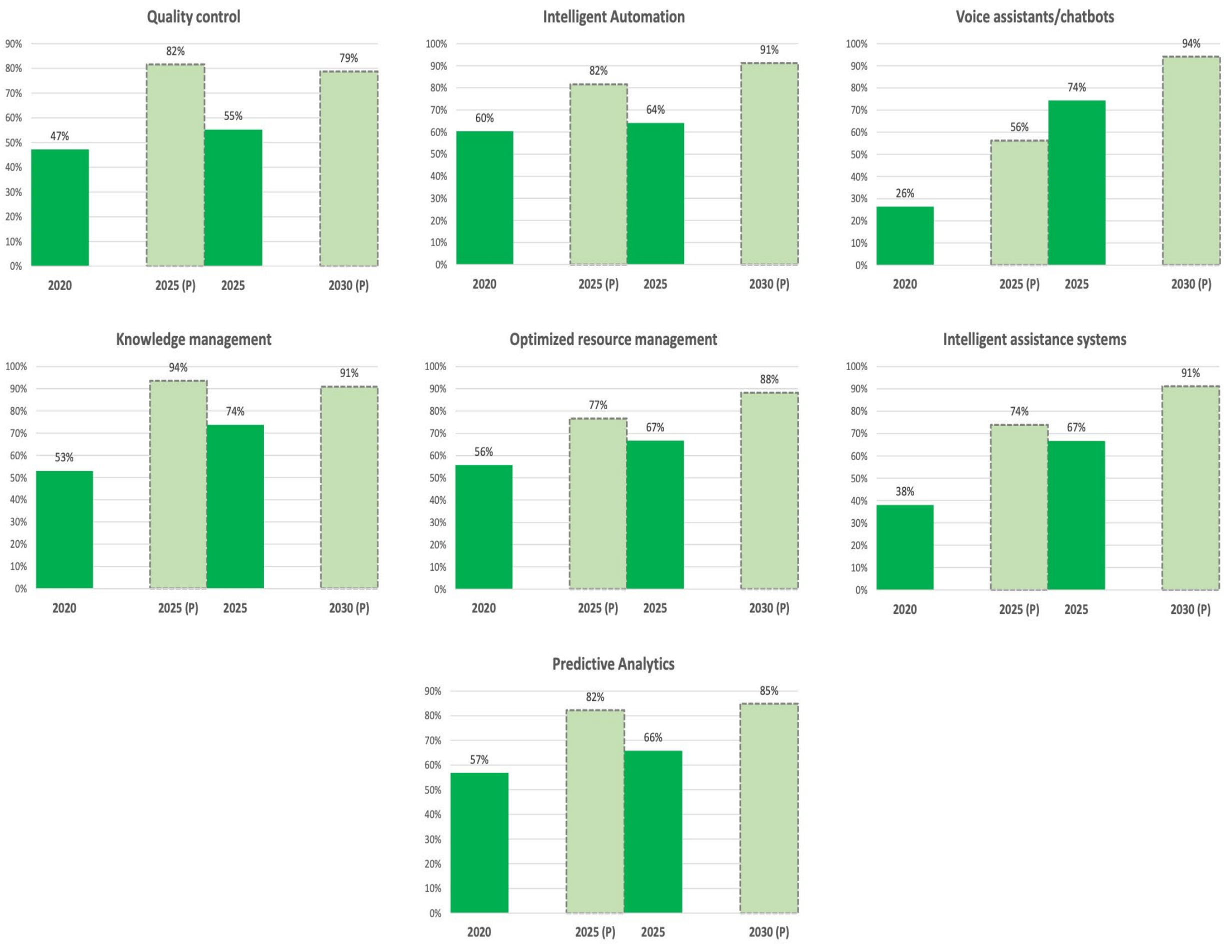

Figure 8 Visualization of results to the “How relevant are the AI topics listed below for your company now compared to the future?”, 2020 and 2025. The dark green bars correspond to current values in 2020 (bar on the left) and 2025 (bar on the right). The light green bars with the dashed line correspond to the forecast of the 2020 survey (bar on the left) and the forecast of the 2025 survey (bar on the right).

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The relevance of all AI-related topics listed in the questionnaire increased between 2020 and 2025. The largest increases were observed for topics related to or influenced by generative AI, such as voice assistants/chatbots, intelligent assistance systems, and knowledge management. For voice assistants and chatbots specifically, participants in the 2020 survey underestimated the actual relevance of this topic by 18 percentage points. However, participants in the 2020 survey generally overestimated the relevance of AI for most other topics, particularly those related to material flow, production, or analytical AI with a focus on well-structured data (including intelligent automation, optimized resource management, predictive analytics, and quality control). This may reflect the inherent challenges in further optimizing production processes, where AI can certainly assist, but is often just one tool among several.

We further observe that participants in the 2025 survey expect the importance of most of these topics to increase markedly by 2030. The estimated increases for most topics are similar in magnitude to those predicted for the period 2020-2025. Based on the comparison between the 2025 forecast and actual data, we speculate that the actual increase by 2030 may not fully match these expectations.

To gain a better understanding of the obstacles to further AI implementation in companies, we asked survey participants the open-ended question, "What obstacles do you see for the use of AI in your company?" (data not shown; details are provided in the supplementary materials).

Analysis of the open-ended responses indicates that all categories previously identified as obstacles to digitalization were also considered barriers to AI adoption. Six additional categories specific to AI were mentioned: (1) IT security/ data protection, (2) lack of trust/control, (3) insufficient digitalization, (4) lack of data, (5) missing knowledge about applications, and (6) not in line with company philosophy. Interestingly, the latter two categories were absent from the 2025 survey results, which may be attributed to the rise of generative AI since 2022. This shift appears to have prompted more intensive engagement with AI within companies, leading to sufficient knowledge regarding its use (at least for generative AI) and a changing perception – AI is no longer seen as an "impurity", to use a chemical term, in company philosophy, though it has certainly not yet become a core part of every company's identity.

The most prominent obstacle reported by survey participants in 2025 was IT security and data protection. This points to an increased sensitivity around balancing the need to protect confidential information with the large data requirements of AI applications. This heightened awareness is further reflected in the emergence of the category „lack of trust/control" in 2025, which was not mentioned in 2020.

We complemented this analysis by asking the question, „How relevant are the following obstacles for the use of AI in your company?" and specifying different topics we anticipated would be relevant in this context. The results are presented in Figure 9.

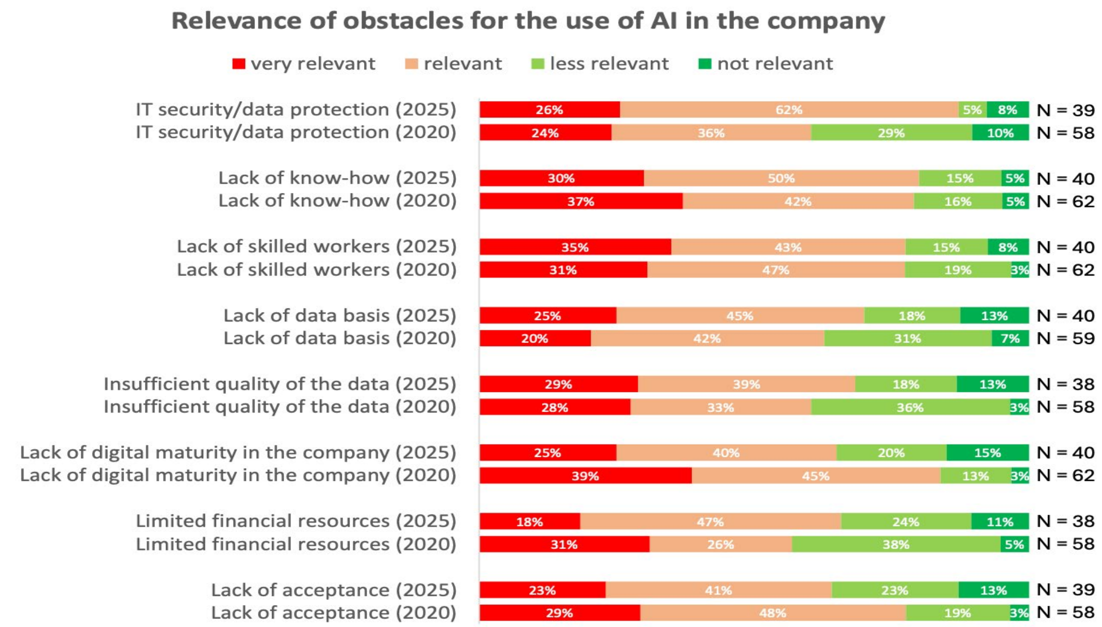

Figure 9 Visualization of results to the question "How relevant are the following obstacles for the use of AI in your company?", 2020 and 2025.

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According to survey participants, all of the specified topics are obstacles for the further expansion of AI within companies. IT security and data protection was identified as the most significant obstacle, with 88% of respondents stating it was very relevant or relevant. Notably, the importance of this obstacle has increased by 28 percentage points since 2020. Other categories, while still important, have generally remained at a similar level or decreased slightly when considering the combined "very relevant" and "relevant" responses. Most interestingly, there was a modest decrease in the obstacles "lack of acceptance" (from 77% in 2020 to 64% in 2025) and "lack of digital maturity in the company" (from 84% in 2020 to 65% in 2025).

This aligns well with the results shown in Table 1 and the observation that companies have increased their digitalization efforts since 2020, likely influenced by the Covid-19 pandemic as well as the gradual adoption of generative AI.

When examining the obstacles by company size (see Fig. 10), we observe that companies with fewer than 50 employees considered most obstacles less significant in 2025 compared to 2020. For companies with more than 1,000 employees, the average assessment of individual obstacles remained largely unchanged between 2020 and 2025, with a slight increase reported for "IT security/data protection" and a slight decrease for "lack of digital maturity in the company."

Figure 10 Share of answers with "very relevant" and "relevant" of total number of answers to the question "How relevant are the following obstacles for the use of AI in your company?" for different company sizes, 2020 (dashed line) and 2025 (solid line).

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Companies with 50-999 employees considered most obstacles to be more important in 2025 compared to 2020, particularly regarding financial resources, lack of skilled workers/know-how, and a lack of sufficiently high-quality data. They also reported that IT security/data protection had increased in importance. Conversely, lack of acceptance was less of an obstacle in 2025 than in 2020.

Comparing the results between company sizes shows that the pattern in 2020 was quite similar across all companies (see Fig. 11). Although there are some deviations from the average, the overall pattern remains comparable between different company sizes. We believe this may be due to the fact that, in 2020, AI applications were primarily focused on process optimization, process automation, and data analysis – activities that are central to chemical and pharmaceutical companies. It is therefore not surprising to see a similar assessment across companies of different sizes during that period.

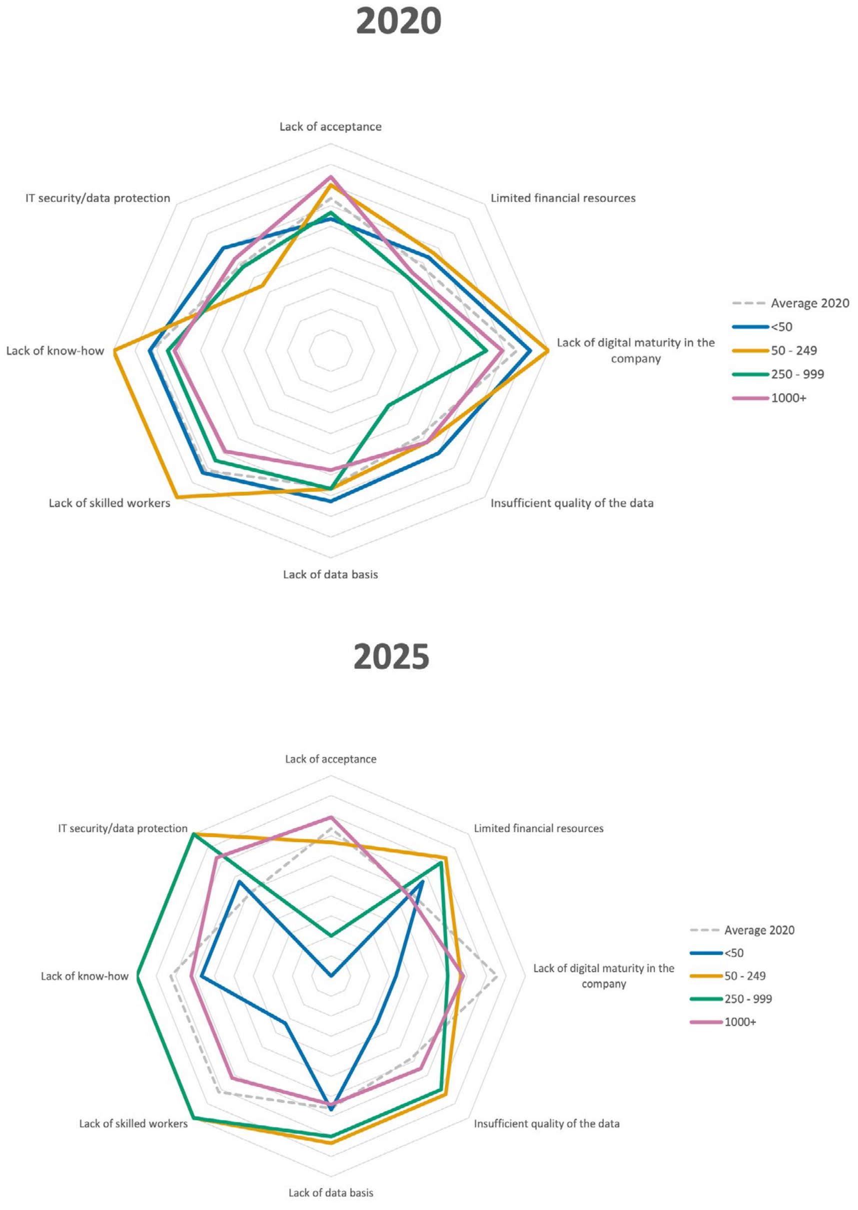

Figure 11 Comparison of "obstacle pattern" between different company sizes from survey 2020 and 2025.

When looking at the results of the 2025 survey, we observe a greater variation in the assessment of obstacles between companies of different sizes. Companies with fewer than 50 employees and those with more than 1,000 employees reported a comparable or even lower relevance for most obstacles. In contrast, companies with 50-999 employees appear to face greater challenges in adopting AI.

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4 Discussion

4.1 Evolution of Digitalization and AI Adoption

Results show a steady rise in the use and importance of digital technologies. By 2025, 91% of companies rated digitalization as "relevant" or "very relevant", up from 75% in 2020. This reflects broader industry trends catalyzed by the Covid-19 pandemic and improved digital infrastructure. AI adoption also increased markedly, from 34% to 76%, indicating a shift from pilot projects in analytics and automation to broad integration of generative AI tools. AI is now seen not only as a tool for data analysis, but increasingly as a facilitator of everyday tasks and communication. These findings match previous reports of widespread AI use in the sector (Chiang, 2022; Patel, 2022).

4.2 Trajectory and Momentum: Short-term Overestimation and Long-term Potential

The survey reveals that respondents in 2020 overestimated the short-term operational impact of several AI topics for 2025. This pattern is consistent with Amara's Law: "We tend to overestimate the effect of a technology in the short run and underestimate the effect in the long run" (Amara, 2007). The underlying tendency for experts to misjudge technology adoption rates is well documented (Rahal et al., 2021; Naudé, 2021; Bonaccorsi et al., 2020) and highlights persistent cognitive biases in technology foresight. Early predictions about AI relevance in areas like predictive analytics, automation, resource, and knowledge management were only partially realized; meanwhile, disruptive generative AI applications, barely considered in 2020, have become central by 2025. These findings suggest that current forecasts for 2030 may also be overestimated, underscoring the need for ongoing, data-driven monitoring of technological trends.

4.3 Sectoral Differences and the "Mittelstand Challenge"

A key finding is the heterogeneity of digital and AI adoption by company size. Large enterprises and some small firms (<50 employees) show advanced digitalization and AI use, while medium-sized companies ("Mittelstand", 50-999 employees) lag behind and face more obstacles, including limited financial resources, lack of qualified staff, data quality issues, and technical challenges like IT security and system integration. This aligns with previous research (Fraunhofer ISI and IW Consult, 2024).

The persistence – and in some cases intensification – of these challenges suggests that the "Mittelstand", a key part of Germany's industrial base, risks structural disadvantages in digital transformation. Without action, this divergence may reduce overall sector competitiveness and innovation. Possible causes include budget constraints, shortage of skilled workers, and lower strategic prioritization of digital initiatives compared to larger corporations. If these hypotheses hold, our findings highlight the need for targeted support measures, best-practice sharing, and further research to develop tailored solutions for medium-sized companies.

4.4 Barriers to Further Implementation: Technical, Organizational, and Cultural Factors

The landscape of obstacles has shifted: while earlier barriers focused on mindset, budgets, and digital literacy, by 2025 technical and organizational issues predominate. IT security and data protection are now the leading concerns (cited by 88% of respondents), reflecting both the complexity and data demands of advanced AI, and evolving regulations such as DSGVO. Reluctance caused by lack of acceptance or digital maturity is decreasing. Organizations seem to be more ready to embrace digital change.

4.5 Implications and Future Directions

The sector is in transition: digitalization and AI have shifted from isolated experiments to integrated, business-critical roles, with generative AI – especially large language models and assistants – acting as a major catalyst from 2020 to 2025, notably in R&D and customer engagement. Despite progress, major barriers persist, particularly for medium-sized enterprises, and expert forecasts remain vulnerable to short-term overoptimism.

Ongoing empirical research is needed to track these trends and challenges. Enhanced collaboration among industry, academia, and policymakers is crucial to drive inclusive digital transformation. Given the importance of SMEs in the sector, we hope our results will prompt targeted support, upskilling, and practical solutions for overcoming obstacles. Future studies – including a potential follow-up in 2030 – will be important to validate forecasts and deepen understanding of the ongoing technological change.

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Supplementary Material

This section contains detailed information about three open-ended questions from the 2020 and 2025 surveys that are not included in the main article:

1. “What major obstacles do you see in your company with regard to digitalization?”
2. “How exactly is AI used in your company?”
3. “What obstacles do you see for the use of AI in your company?”

This information complements the data in the main article and the interested reader can find additional information on the mentioned subjects.

Table S1 Classification of open-ended responses to the question “What major obstacles do you see in your company with regard to digitalization?”.

Obstacle	*Number of answers in Survey 2020*	*Exemplary Answers from Survey 2020*	*Number of Answers in Survey 2025*	*Exemplary Answers from Survey 2025*
Lack of mindset	22 (22.0%)	„Acceptance in middel management is a big issue“ „Management level too old“ „There is a lack of innovative and open-minded people in the important positions in the company“ „The acceptance of the new opportunities is very reluctant amony many older employees“	6 (11.1%)	„Average age of the company is quite high, resulting in inflexible employees/ colleagues and little willingness to embrace new technology/digitalisation“ „Some older employees who find it difficult to change.“
Lack of skills	15 (15.0%)	“Too few skilled workers“ „Lack of employee skills“ „Shortage of skilled workers“	12 (22.2%)	„Recruiting IT specialists“ „Acquisition of the required specialists for the development of digitalization tools“ „There is hardly any staff available to deal with digitization issues“
Complexity of change process	10 (10.0%)	“Distribution across multiple locations leads to challenges in global structural digitalization.” “Employee training (time, costs).”	11 (20.4%)	“Keeping pace with dynamic development is difficult for medium-sized businesses.” “Transformation of work processes for employees over the age of 50.”

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Obstacle	*Number of answers in Survey 2020*	*Exemplary Answers from Survey 2020*	*Number of Answers in Survey 2025*	*Exemplary Answers from Survey 2025*
Complexity of IT landscape	12 (12.0%)	"Very heterogeneous landscape of IT tools." "Avoid over-digitization (multiple programs for same task)." "Harmonization of software solutions."	7 (13.0%)	"Isolated solutions in the IT landscape." "Complexity, number of existing systems, many interfaces."
Lack of budget / resources	20 (20.0%)	"Too high costs." "Diverting capital from ongoing business." "Excessive costs for implementation, maintenance, repair, data backup."	6 (11.1%)	"Limited own resources (personnel and investment)." "Own financial expenditure, which must be made as an advance payment."
Lack of strategy / coordination	5 (5.0%)	"No strategy for digitalization." "Lack of coordination."	5 (9.3%)	"Lack of coordinated process management." "Uncertainty regarding responsibilities." "Lack of leadership, no plan."
External factors	13 (13.0%)	"Bandwidth in some regions and information security." "The infrastructure in Germany is poorly developed."	2 (3.7%)	"Many regulatory requirements must be complied with." "Makes it difficult to implement new ideas."
Other	3 (3.0%)	"Non-network-capable analyzers."	5 (9.3%)	"Processing large amounts of data." "Fast implementation without long offline phases."

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Table S2 Classification of open-ended responses to the question "How exactly is AI used in your company?".

Application	Number of answers in Survey 2020	Exemplary Answers from Survey 2020	Number of Answers in Survey 2025	Exemplary Answers from Survey 2025
Data analysis / Forecast	15 (62.5%)	"Provision calculation" "Analysis of big data (images, texts, numbers)" "Pricing, planning/ forecast" "Prediction of material properties"	0 (0.0%)	-
Process optimization / Automation	5 (20.8%)	"Use for human decision-making in raw material procurement based on extensive data""Improvement of production processes."	4 (11.1%)	"Control of machines, systems, vehicles." "Evaluation of defects on components by a camera-supported unit."
Generative AI	0 (0.0%)	-	20 (55.6%)	"ChatGPT for creating/ summarizing documents, verifying theses." "Preparation of plans and technical concepts." "Use of LLMs such as MS Copilot and ChatGPT in software development." "Company GPT based on ChatGPT with internal data."
Innovation / R&D	3 (12.5%)	"Structural analysis of proteins." "Especially in research and early development (lead structure search)."	4 (11.1%)	"In R&D in software development." "Development of predictive computer models for recipe R&D." "In the research and development of new drugs."
Marketing / Communication	1 (4.2%)	"E-mail marketing to optimize the sending time."	3 (8.3%)	"Customer communication." "Generation of images, video support e.g. for marketing." "In marketing when creating posts, mailings, application reports."
Other	0 (0.0%)	-	5 (13.9%)	"Across wide range of use cases, all functions all businesses." "AI should be used as an assistive technology." "Various activities, but still very limited."

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Table S3 Classification of open-ended responses to the question "What obstacles do you see for the use of AI in your company?".

Obstacle for AI adoption	*Number of answers in Survey 2020*	*Exemplary Answers from Survey 2020*	*Number of Answers in Survey 2025*	*Exemplary Answers from Survey 2025*
IT security / data protection	1 (1.8%)	"Security"	9 (22.5%)	-"We maintain very strict confidentiality between our clients and ourselves. This ensures that client information does not become common knowledge." "Protection of sensitive data"
Lack of budget / resources	10 (17.5%)	"Currently still associated with high costs, to the actual measurable significant added value for the company" "Balance sheet must be correct, i.e. it must be financially worthwhile"	6 (15.0%)	"Lack of finances and human resources for planning and implementation"
Lack of skills	5 (8.8%)	"IT + AI capabilities are not yet 'melted' into the company's DNA" "Competence and qualification of the workforce"	6 (15.0%)	"Personnel that can implement AI" "Digital skills of the workforce" "Verification of the data and information provided for their validity"
Lack of trust / control	0 (0.0%)	-	5 (12.5%)	"AI is in the testing phase and not yet very trustworthy for me." "Missing control systems for AI"
External factors	1 (1.8%)	"Regulatory requirements"	3 (7.5%)	"Regulatory requirements require 'Explainable AI'" "GMP regulations"
Lack of mindset	9 (15.8%)	"The old management level would have to be convinced of the benefits of digitalization" "Lack of willingness of the workforce" "Key elements in management do not want to implement AI consequences" "People prefer to talk and interact with people"	3 (7.5%)	"Persistence of the organization" "To involve employees over 50 years of age"

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Obstacle for AI adoption	*Number of answers in Survey 2020*	*Exemplary Answers from Survey 2020*	*Number of Answers in Survey 2025*	*Exemplary Answers from Survey 2025*
Complexity of change process	3 (5.3%)	"It simply takes time to translate current processes into algorithms. Everyone handles tasks differently. There's no recipe for success."	2 (5.0%)	"It must be constantly trained."
Complexity of IT landscape	3 (5.3%)	"Too many different IT systems"	1 (2.5%)	"Combining different IT systems to integrate information."
Insufficient digitization	2 (3.5%)	"The current infrastructure does not support the use of AI" "Lack of basic digitalization."	1 (2.5%)	"Missing foundations, e.g. data classification and partial lack of written/documented knowledge."
Lack of strategy / coordination	4 (7.0%)	"Lack of a group-wide digital strategy."	1 (2.5%)	"Expectations within company are not aligned."
Lack of data	3 (5.3%)	"Reliability of source data" "Data quality as a basis for suitable AI models."	1 (2.5%)	"Preparation of the data so that it can be processed compliantly."
Missing knowledge about application	8 (14.0%)	"One hurdle is the lack of a problem definition." "Too little knowledge about AI itself and its possible applications."	0 (0.0%)	-
Not in line with company philosophy	2 (3.5%)	"AI is not currently reflected in the essence of the company's purpose."	0 (0.0%)	-
Other	6 (10.5%)	"Our products are customized for each customer, requiring a high degree of specialization." "Since these are chemicals, the use of AI would be too dangerous."	2 (5.0%)	"Language barriers within the company (Korean-English-German)."

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Research Paper

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Employer attractiveness in the Chemical Industry: Investigating the impact of product novelty, product relevance, and work meaningfulness

While research on employer attractiveness has traditionally focused on external employer branding, less is known about what attracts employees to stay. This study examines how product-related factors—specifically perceived novelty and societal relevance—relate to internal employer attractiveness, and whether these relationships are mediated by meaningful work. We develop and test a mediation model using two-wave survey data from 138 employees of a global chemical company. Results show that perceived product novelty has a significant positive relationship with employer attractiveness, partially mediated by meaningful work. Perceived product relevance, however, does not show a direct relationship, but an indirect one via meaningful work. These results highlight that perceived product characteristics - beyond traditional HR instruments - can contribute to how employees evaluate their employer. The study extends the internal employer branding literature by integrating product-driven perceptions and meaningfulness into the understanding of organizational attractiveness.

Keywords: Employer attractiveness, Product relevance, Product novelty, Product innovation, Meaningful work, Internal employer branding, Employee perception

Introduction

Customers will never love a company until the employees love it first. (Simon Sinek)

The literature on how to position organizations as attractive employers has been intensively developed during the last decades since Ambler and Barrow (1996) published a study focusing on **employer branding**, meaning the actions undertaken by an organization to develop employer knowledge (Theurer et al., 2018). The outcome of activities to enhance the employer brand is a "package of functional, economic and psychological benefits provided by employment and identified with the employing company" (Ambler and Barrow, 1996, p. 187).

Turban and Greening (1997) introduced the term **employer attractiveness** as the degree to which a respondent would personally seek an organization as an employer. Berthon et al. (2005) concluded that there was a high similarity between the **employer brand** and internal employer branding. They showed that employees are attracted to their employers based on the five dimensions: economic value (compensation

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and benefits, job security, and opportunities for promotion), development value (recognition, self-worth, confidence, and future employment), interest value (exciting work environment, e.g., innovative products and services), social value (a fun-oriented and happy working environment, team atmosphere, etc.), and application value (opportunity to apply as well as teach others what was learned). Turban and Cable (2003) argue that applicants lack the experience of working in the target organization yet, and their perceptions might not provide complete and accurate information about the employment experience. This distinction between applicants and employees laid the foundation for later research, which began to explore employer attractiveness from the perspective of the workforce of an organization. From a signalling perspective (Spence, 2002; Lievens and Highhouse, 2003), organizations rely on observable cues to communicate their attractiveness, yet once employees are inside, such signals are complemented and reinterpreted through daily work experiences.

Over the following decades, the main focus of research remained on applicants rather than on the perception of those already working in an organization (Lievens and Highhouse, 2003; Lievens et al., 2007). More recent studies with employees have mostly highlighted HR-related drivers such as work atmosphere, training and development, ethics and CSR (Corporate Social Responsibility), or compensation and benefits (e.g., Tanwar and Prasad, 2017; Maurya and Agarwal, 2018; Vnouckova et al., 2018). These findings underline that HR practices are crucial, but they leave open the question of whether other factors that differentiate organizations, such as organizational products themselves, influence how employees perceive their employer.

This omission is noteworthy because employees, like customers, are constantly exposed to their organization's products and services. Branding research suggests that product attributes such as novelty and societal relevance are central to how stakeholders evaluate organizations (Aaker and Shansby, 1982; Aaker, 2004). Aaker (2004), in particular, emphasizes that corporate brands embody organizational values, innovation, and citizenship programs, and that these associations are vital for internal brand building. Extending this logic to the employee perspective suggests that product attributes may also shape employer attractiveness beyond traditional HR signals.

Against this background, we focus on two product dimensions that are theoretically grounded and directly relevant for employees' evaluations: **product novelty** and **product relevance**. Product novelty reflects perceptions of innovation and vitality, signalling to employees that the organization is dynamic and future-oriented. Product relevance reflects the perceived societal value of products, signalling a broader purpose and contribution to society. Both dimensions are well established in branding and innovation research (e.g., Aaker, 2004; Sommer et al., 2017), but they have not been systematically examined in relation to employer attractiveness among employees. Further, drawing on a signaling theory (Spence, 2002) and a sensemaking perspective (Weick, 1995), we argue that meaningful work, defined as work that is perceived as particularly significant and holding a positive meaning (Rosso et al., 2010), is an important mediating mechanism explaining the relationships between perceive product characteristics and employer attractiveness. Specifically, perceived product novelty and relevance would enable would enable people feel sense of pride and contribution enabling experiencing meaningfulness at work (Glavas & Lysova, 2025; Pratt & Ashforth, 2003).

By introducing perceived product novelty and relevance, our study makes three contributions. First, we extend the employer attractiveness literature by moving beyond HR-related factors and incorporating product-based perceptions as additional factors (Berthon et al., 2005; Tanwar and Prasad, 2017; Maurya and Agarwal, 2018; Vnouckova et al., 2018; App and Buettgen, 2016; Uen et al., 2015). Second, we theorize that the effects of perceived product attributes are mediated by employees' sense of meaningful work, thereby linking branding insights (Aaker, 2004) to organizational behavior research concerned with how meaningful work can be fostered in organizations (Lysova et al., 2019; Rosso et al., 2010). Third, we study a critical case in the chemical industry—a sector often described as a "dirty industry"—to show that perceived product innovation and societal contribution can strengthen the internal employer brand even under challenging external conditions (King and Lenox, 2000).

Taken together, this study addresses an important gap by integrating product-related perceptions into the understanding of employer attractiveness from the employee perspective. We argue that perceived product novelty and perceived product relevance, alongside

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meaningful work, provide a more complete picture of what makes an employer attractive to its workforce.

This article is structured as follows. In the next section, we develop our theoretical framework and hypotheses concerning the role of perceived product novelty, perceived product relevance, and meaningful work for employer attractiveness. We then describe our research design, data collection, and measures, followed by the presentation of results. Finally, we discuss theoretical and practical implications, outline limitations, and suggest directions for future research.

Theoretical Framework and Hypothesis

Our theorizing and hypotheses are formulated at the individual level of analysis, i.e., they concern employees' perception of product novelty and product relevance, and how these perceptions relate to employer attractiveness via meaningful work.

Employer attractiveness of an organization

Since Ambler and Barrow (1996) foundational exploratory study "The employer brand", testing the application of brand management techniques to human resources (HR) with interviews with HR professionals, the topic of employer brand and employer attractiveness has constantly developed into a field of interest to researchers and practitioners. Employer brand is defined as "the package of functional, economic and psychological benefits provided by employment, and identified with the employing company" (Ambler and Barrow, 1996, p. 187). While Amber and Barrow had already in their work suggested a relationship between employees, word of mouth and successful recruiting of new employees, early research mostly focused on employer attractiveness as perceived by applicants and not by employees of an organization (Dassler et al., 2022; Lievens and Highhouse, 2003).

Following the research of Ambler and Barrow (1996), there have been numerous studies investigating the concept of attributes and outcomes of an attractive employer (e.g. Lievens and Highhouse, 2003; Backhaus and Tikoo, 2004; Berthon et al., 2005). Organizational attractiveness or employer attractiveness is regularly defined as the benefits applicants anticipate from working for a specific organization (Berthon et al., 2005). Organizational attractiveness is also considered the power that encourages employees to stay, as well as the degree to which employees and applicants perceive the organization as a good place to work. It is posited that companies with strong employer brands can reduce the cost of employee acquisition, improve employee relations, and increase employee retention (Berthon et al., 2005). The values provided by an employer can be differentiated into social, development, application, safety, and economic values (Berthon et al., 2005). In exchange for the values provided by an organization, employees not only dedicate their working hours. Research indicates that different levels of those values also have positive outcomes like employee engagement and identification (Schlager et al., 2011), linking employer attractiveness to the literature around employee engagement and identification.

Over the past decades, the main focus of the research has been on employer attractiveness in the eyes of applicants (Dassler et al., 2022). The specific perspective of employees, however, differs significantly from the perspective of applicants. According to signalling theory (Spence, 2002), in contexts with asymmetric information, actors rely on observable signals to form judgments about otherwise unobservable qualities. Applied to organizations, employer branding activities serve as signals that shape outsiders' perceptions (Lievens and Highhouse, 2003). For applicants, such signals are especially important because they lack direct experience with the organization. In contrast, employees gradually replace external signals with their own experiences. This raises the question of whether other signals—such as the nature of the organization's products—continue to shape how employees perceive their employer once they are inside the firm.

Although employees have richer information than applicants, much of the organizational environment remains uncertain or ambiguous, for example with respect to long-term strategy, future product pipeline, or market prospects. In such contexts of residual information asymmetry, product characteristics continue to function as organizational signals (Spence, 2002). Employees then actively interpret these signals through sensemaking processes (Weick, 1995), which shape their evaluation of meaningful work and, ultimately, employer attractiveness.

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Perceived product novelty, perceived product relevance, and employer attractiveness

Products and services are an integral part of any organization, not only for customers but also for employees. Aaker (2004) emphasized that corporate brands derive their strength from organizational associations such as innovation, vitality, and societal contribution. These product-related associations are not limited to external stakeholders but can also be internalized by employees as part of their evaluation of the organization. From a signalling perspective (Spence, 2002), products serve as visible cues that communicate qualities of the organization. Innovative and socially impactful products may signal vitality, credibility, and purpose, thereby shaping how employees perceive their employer. Thus, products can be understood as organizational signals that provide input into employees' evaluations of their employer. This reasoning is consistent with research that links symbolic attributes such as innovativeness and progressiveness to employer attractiveness (Lievens and Highhouse, 2003; Sommer et al., 2017) as well as studies connecting corporate social responsibility to employees' organizational identification (Klimkiewicz and Oltra, 2017; Pratt and Ashforth, 2003).

Against this background, we focus on two product dimensions that are theoretically grounded and directly relevant for employees' evaluations: perceived product novelty and perceived product relevance. Perceived product novelty signals organizational competence, adaptability, and forward momentum, attributes that employees interpret as indicators of long-term viability and professional pride (Spence, 2002; Aaker, 2004). Novel products demonstrate that the organization is dynamic and future-oriented, which enhances employees' sense of belonging to a successful and innovative employer. Prior work confirms that symbolic attributes such as innovativeness and prestige positively influence organizational attractiveness (Lievens and Highhouse, 2003; Sommer et al., 2017). Thus, we propose:

Hypothesis 1: Perceived product novelty positively relates to the internally perceived employer attractiveness.

Perceived product relevance captures the extent to which employees see their organization's products as useful, valuable, and beneficial for society. Such perceptions provide employees with a sense that their daily work contributes to a greater purpose beyond economic outcomes. In signalling terms (Spence, 2002), relevant products communicate that the organization is committed to societal needs, which strengthens employees' identification with the firm. This logic is consistent with prior CSR research showing that employees derive meaningful work when they perceive their employer as contributing to the common good (Aguinis and Glavas, 2019; Glavas and Lysova, 2025; Klimkiewicz and Oltra, 2017). Thus, we propose:

Hypothesis 2: Perceived product relevance positively relates to the internally perceived employer attractiveness.

Perceived product novelty, perceived product relevance and meaningful work

Meaningful work refers to "work experienced as particularly significant and holding more positive meaning for individuals" (Rosso et al., 2010, p. 95). Prior research emphasizes that meaningful work arises from alignment between individual motives and organizational contexts (Pratt and Ashforth, 2003; Lysova et al., 2019; Bailey et al., 2019). In this context, CSR is commonly defined as "context-specific organizational actions and policies that take into account stakeholders' expectations and the triple bottom line of economic, social, and environmental performance" (Aguinis and Glavas, 2012, p. 933). CSR has also been shown to provide employees with opportunities to experience their work as contributing to a greater good, thereby functioning as an important contextual source of meaningful work (Aguinis and Glavas, 2019; Glavas and Lysova, 2025).

Extending this logic to product-related factors, we argue that perceived product novelty and perceived product relevance can both function as organizational signals that foster meaningful work. Novelty conveys vitality and innovativeness, which can generate employee pride and sense of contribution to a dynamic organization. Relevance, in contrast, parallels insights from CSR research by signalling that products serve societal needs, thereby strengthening employees' experience of purpose and meaningfulness in their work. Based on these theoretical arguments, we hypothesize:

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Hypothesis 3: Perceived product novelty is positively related to meaningful work.

Hypothesis 4: Perceived product relevance is positively related to meaningful work.

Research consistently shows that meaningful work is a central component of positive organizational experiences. For example, employees who perceive their work as meaningful report higher engagement, stronger organizational identification, and greater commitment (Bailey et al., 2019; Allan et al., 2019). When employees believe that their work contributes to a greater purpose, they are more likely to develop positive attitude toward their employer and see the organization as a desirable place to stay. Prior research also indicates that meaningful work strengthens organizational identification and reduces turnover intentions, both of which are closely linked to perceptions of employer attractiveness (Allan et al., 2019; Lysova et al., 2019). Thus, meaningful work represents a key pathway. Based on this reasoning, we propose:

Hypothesis 5: Meaningful work is positively related to the perceived employer attractiveness.

From a signalling perspective (Spence, 2002), product characteristics provide observable cues of organizational qualities such as innovation, vitality, or societal contribution. However, signals alone are not sufficient to shape employer attractiveness. Employees actively interpret these signals through sensemaking processes (Weick, 1995), which shape their experience of meaningful work. In case of perceived product novelty, employees may interpret innovative products as evidence that their organization is dynamic, future-oriented, and successful. This fosters pride and vitality in their work, which translates into stronger sense of meaningfulness. In turn, meaningful work makes the organization more attractive to employees, above and beyond the direct effect of perceived product novelty. We therefore hypothesize:

Hypothesis 6: The relationship between perceived product novelty and perceived employer attractiveness is mediated by meaningful work.

In case of perceived product relevance, employees may interpret socially valuable products as a signal that the organization contributes to societal needs and the common good. Such products create purpose at work, which strengthens employees' sense of meaningfulness. It is through this experience of meaningful work, rather than a direct effect, that perceived product relevance enhances employer attractiveness. Thus, we propose:

Hypothesis 7: The relationship between perceived product relevance and perceived employer attractiveness is mediated by meaningful work.

Methods

Research setting

The empirical context of this study is a global chemical manufacturing company with more than 30,000 employees worldwide. It serves as an appropriate research setting for testing our hypotheses for several reasons. First, the company consists of different business divisions with products varying from very mature products to very innovative or new products. Second, the company's products are solely sold to other manufacturing companies and not directly to end-customers. Therefore, it is difficult to identify with the products, e.g., a certain chemical substance. A positive correlation with employer attractiveness likely has an even greater effect on consumer goods. Third, several recent product innovations can also be considered to serve the trend of sustainability by being "green" alternatives to the more traditional chemical products of the company. Accordingly, we expected to observe sufficient individual variance in our model.

Data collection and sample description setting

Procedure

The level of analysis in this study is the individual employee. To collect data, we reached out to the HR department of the company, who supported us by sending out the survey (see Table 1, Appendix) to 1,500 randomly selected employees from three globally operating business divisions. We collected the data in two waves during the period between April to October 2021. The first primary data (T1) was collected in June 2021, and the second data collection (T2) was conducted

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in September and October 2021, two months after the primary data collection. For both data collections, the same 1,500 employees were contacted via an online survey that was distributed through email, including the information that the data collection with the same questions will be ran twice. Surveys were administered in German and English, the two main working languages of the company. To ensure conceptual equivalence across languages, we followed a standard translation–back translation procedure (Brislin, 1980). All survey items were first translated from English into German by a bilingual researcher, and then independently back-translated into English by another bilingual researcher. Discrepancies were discussed and resolved in consultation with the research team to ensure accuracy and consistency of meaning.

Out of a total of 1,500 surveys sent out globally, we received usable responses from 246 employees (16.4% response rate) in summer 2021 and from 226 (15.1% response rate) in fall 2021. A total of 138 usable responses (9.2% response rate) were collected from the same respondents at both collection waves. For both data collections, we tested for nonresponse bias by comparing key attributes of respondents and non-respondents.

Sample

Participants of the final sample (n = 138) were 138 working adults from across the globe. Of the participants who answered the items, 85 (62%) were men and 52 (38%) were women; with a mean age of 39.33 (Range = 21 – 52, SD 8.72). Regionally, 87 (63%) were based in Europe, the Middle East and Africa, including Germany, 34 (25%) were based in the Americas, and 17 (12%) were located in Asia. Participants were asked to voluntarily select their main area of work, with the majority indicating they work in production (37, 27%), 25 (18%) worked in administration and 10 (7%) worked in research, while the remaining indicated “other”. The majority of participants (79, 57%) had more than three years of work experience.

Measurement, construct validation and control variables

All variables were measured using five-point Likert scales (1 = strongly disagree to 5 = strongly agree), and their order here follows the presentation in Tables 2 and 3 (see Appendix).

Employer attractiveness. The perception of employer attractiveness (T2) was measured with a four-item scale adapted from Highhouse et al. (2003), who introduced a framework to measure attraction to organizations along three dimensions: general attractiveness, intention to pursue and prestige. We adapted the five items from the general attractiveness dimension to the four items used in our research, e.g., ‘For me, this organization is a good place to work’. Reliability analysis indicates that the scale has good internal consistency, with a Cronbach’s alpha of 0.90.

Perceived product novelty. Perceived product novelty (T1) was measured using the three-item scale that Story et al. (2014) used to describe product innovation and novelty, e.g., ‘Relative to our main competitors, the products this organization offers in the target market(s) are radical’. Reliability analysis indicates the scale is internally consistent, with a Cronbach’s alpha of 0.71.

Perceived product relevance. Perceived product relevance (T1) was measured with the adapted scale of Im et al. (2015), by using four of the items that were used to measure relevance for customers. We replaced ‘customer’ with ‘society’, e.g. ‘This organization’s products are useful for society’. Reliability analysis indicates that the scale has good internal consistency, with a Cronbach’s alpha of 0.90.

Meaningful work. Meaningful work (T2) was measured using the ten-item scale of the Work and Meaning Inventory (WAMI; Steger et al., 2012). The scale consists of three dimensions: positive meaning, e.g., ‘I have found a meaningful career’, meaning making through work, e.g., ‘I view my work as contributing to my personal growth’ and greater good motivations, ‘I know my work makes a positive difference in the world’. We used an aggregated score of meaningful work. Reliability analysis indicates the scale has good internal consistency, with a Cronbach’s alpha of 0.91.

Control variables. We included factors that prior research identified as important for employer attractiveness (Berthon et al., 2005). Specifically, we measured social value, economic value, development value, application value. These items do not represent subdimensions of our dependent variable but capture alternative explanatory factors that could influence attractiveness perceptions. These controls allowed us to examine the unique contribution of product-related variables beyond established HR-related drivers. We controlled for age

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and gender since the work of Albinger and Freeman (2000) and Reis and Braga (2016) indicates that female and male applicants of different generations may assess organizational attractiveness factors differently. We included job level as a control variable because the relevance of prestige attributes like products may be more important the higher an employee ranks within an organization. Lastly, we controlled for the functional area of the job because functions may differ in the extent to which they are exposed to products.

We used multiple ordinary least squares regressions to check for compliance with Baron and Kenny's (1986) four requirements for mediation: (1) the independent variables significantly predict the dependent variable; (2) the independent variables significantly predict the mediating variable; (3) the mediating variable significantly predicts the dependent variable; and (4) when the mediating variable is introduced, the effect of the independent variables on the dependent variable is significantly reduced, and the mediating variable significantly accounts for the variability in the dependent variable. Model 1 shows the effects of the control variables, while with Models 2 and 3, we test the first mediation requirement. Models 4 and 5 represent the second requirement of the mediation analysis, and Models 6 and 7 represent the third and fourth requirement. Finally, Model 8 included both, perceived product novelty and perceived product relevance simultaneously and tested for potential omitted-variable bias on employer attractiveness.

Analysis and Results

Confirmatory Factor Analysis

A confirmatory factor analysis (CFA) was conducted using the lavaan package in R to test the measurement model consisting of four latent constructs: employer attractiveness, meaningful work, perceived product novelty, and perceived product relevance. The model was estimated using maximum likelihood estimation based on a sample of 138 cases. All standardized factor loadings were positive ($p < .001$), for most items, above recommended threshold of .50; only perceived product novelty (v_554_T1 = .374) showed a marginally lower loading. We decided to retain the full scale for perceived product novelty as originally validated in prior research (Story et al., 2014) to ensure comparability. The remaining loadings ranged from .51 to .89, indicating satisfactory item-factor relationships. Inter-factor correlations were moderate to high (e.g., MW_T2 ~~ PR_T1 = .61; EA_T2 ~~ PN_T1 = .54), supporting convergent and discriminant validity of the constructs. All results are reported in Table 2 (see Appendix).

The global fit indices of the CFA model are marginally below conventional cut-offs : $\chi^2(203) = 431.86$, $p < .001$; CFI = .878; TLI = .862; RMSEA = .090 (90% CI [.079, .102]); SRMR = .080. We compared the hypothesized four-factor measurement model (employer attractiveness, meaningful work, perceived product novelty, and perceived product relevance) with several alternative structures. A one-factor model (all items loading on a single latent construct), a two-factor model (all product items combined; MW and EA combined), and a three-factor model (perceived product novelty and relevance combined) showed substantially poorer fit (CFI < .83, RMSEA > .11). The hypothesized four-factor model (CFI = .878, TLI = .862, RMSEA = .090, SRMR = .080) provided the best representation of the data, outperforming all alternatives (ΔCFI ≥ .05, ΔRMSEA ≥ .03). A robustness test excluding the weakest novelty item ($\lambda = .37$) yielded nearly identical results (CFI = .877, TLI = .869, RMSEA = .095). Results are reported in Table 4 (see Appendix).

Our approach is also backed by research raising caution against interpreting CFA thresholds too rigidly, particularly in smaller samples and models with many items. As Shi et al. (2019) demonstrate, traditional fit indices can systematically underestimate model fit under such conditions. In line with their recommendations, we therefore rely on a combination of evidence, including high factor loadings for most items, satisfactory composite reliabilities (CR > .77), and AVE values above 0.50, all of which support the convergent validity of our constructs.

Descriptive statistics

Statistical analyses were conducted using SPSS (Version 29.0.2.0), including mediation analyses performed with the PROCESS macro (Model 4; Hayes, 2018).

Table 3 (see Appendix) presents descriptive statistics, reliabilities, and correlations among the study variables. Employer attractiveness was positively correlated with perceived product novelty ($r = .42$, $p < .01$), perceived product relevance ($r = .23$, $p < .01$), and meaningful work ($r = .36$, $p < .01$), with the strongest correlation observed for perceived product novelty. Perceived product relevance

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showed a strong correlation with meaningful work ($r = .57$, $p < .01$). Taken together, these results confirm that employer attractiveness is positively related to all central study variables, providing initial support for the hypothesized relationships. Reliability coefficients (Cronbach's α) for multi-item scales are reported on the diagonal.

Hypothesis testing

The results of our analysis for the empirical testing of Hypotheses 1-7 are reported in Table 5 and 6 (see Appendix). We test the proposed mediation framework first by using the procedure outlined by Baron and Kenny (1986). We then quantify the indirect effects and confidence intervals using a bootstrapping approach (Preacher and Hayes, 2008).

A linear regression analysis was conducted to examine the effects of control variables on perceived employer attractiveness (Model 1). The overall model was significant, $F(8, 129) = 2.92$, $p < .01$, and explained approximately 15.3% of the variance in employer attractiveness ($R^2 = .15$). The effect of social value ($\beta = .20$, $p = .024$) and economic value ($\beta = .22$, $p = .012$) was significantly positive, while all other control variables were not statistically significant related to perceived employer attractiveness.

In Model 2, perceived product novelty was added as an independent variable, alongside control variables. The overall model was significant, $F(9, 128) = 5.39$, $p < .001$, and explained 27.5% of the variance in employer attractiveness ($R^2 = .28$). The relationship of perceived product novelty with perceived employer attractiveness was positive and significant ($\beta = .37$, $p < .001$). Thus, Hypothesis 1 was supported.

In Model 3, perceived product relevance was entered as an independent variable, alongside control variables. The overall model was significant, $F(9, 128) = 3.05$, $p = .002$, explaining 17.7% of the variance in perceived employer attractiveness ($R^2 = .18$). Perceived product relevance was not significantly related to ($\beta = .17$, $p = .059$). Thus, Hypothesis 2 was not supported.

In Model 4, we tested the relationship between perceived product novelty and meaningful work, along with control variables. The overall model was significant, $F(9, 128) = 4.48$, $p < .001$, and explained 24.0% of the variance ($R^2 = .24$). Perceived product novelty had a significant positive relation to meaningful work ($\beta = .23$, $p = .005$). Thus, Hypothesis 3 was supported.

In Model 5, of the relation of perceived product relevance to meaningful work was examined, along with control variables. The overall model was significant, $F(9, 128) = 9.80$, $p < .001$, and explained 40.8% of the variance in meaningful work ($R^2 = .41$). Perceived product relevance had a significant and positive relation to meaningful work ($\beta = .50$, $p < .001$). Thus, Hypothesis 4 was supported.

In Model 6, we tested the mediation effects of meaningful work in the relationship between perceived product novelty and perceived employer attractiveness, along with control variables. The model was significant, $F(10, 127) = 6.76$, $p < .001$, and explained 34.7% of the variance in employer attractiveness ($R^2 = .35$). Both perceived product novelty ($\beta = .30$, $p < .001$) and meaningful work ($\beta = .31$, $p < .001$) were significantly related to employer attractiveness. A bootstrapping analysis with 5,000 samples and a 95% confidence interval confirmed a significant indirect effect of perceived product novelty on employer attractiveness through meaningful work ($B = .07$, $SE = .04$, 95% CI [.0133, .1519]). Since both the direct and indirect effects were statistically significant, this indicates that meaningful work partially mediates the relationship between perceived product novelty and perceived employer attractiveness and therefore, our results provide partial support for Hypothesis 6.

In Model 7, we tested the mediating effect of meaningful work in the relationship between perceived product relevance and perceived employer attractiveness. The model was significant, $F(10, 127) = 4.81$, $p < .001$, and explained 27.5% of the variance in employer attractiveness ($R^2 = .28$). Meaningful work was positively and directly related to perceived employer attractiveness ($\beta = .41$, $p < .001$), while the direct effect of perceived product relevance remained to be not significant ($\beta = -.04$, $p = .680$). A bootstrapping analysis (5,000 samples, 95% CI) confirmed a significant indirect effect of perceived product relevance on perceived employer attractiveness via meaningful work ($B = .20$, $SE = .08$, 95% CI [.0738, .3704]). These results provide support for Hypothesis 7.

In Model 8, both perceived product novelty and perceived product relevance were entered simultaneously, along with all control variables. The model was significant, $F(10,127) = 4.93$, $p < .001$, explaining 28% of the variance in employer attractiveness ($R^2 = .28$). The relationship of perceived product novelty with perceived employer

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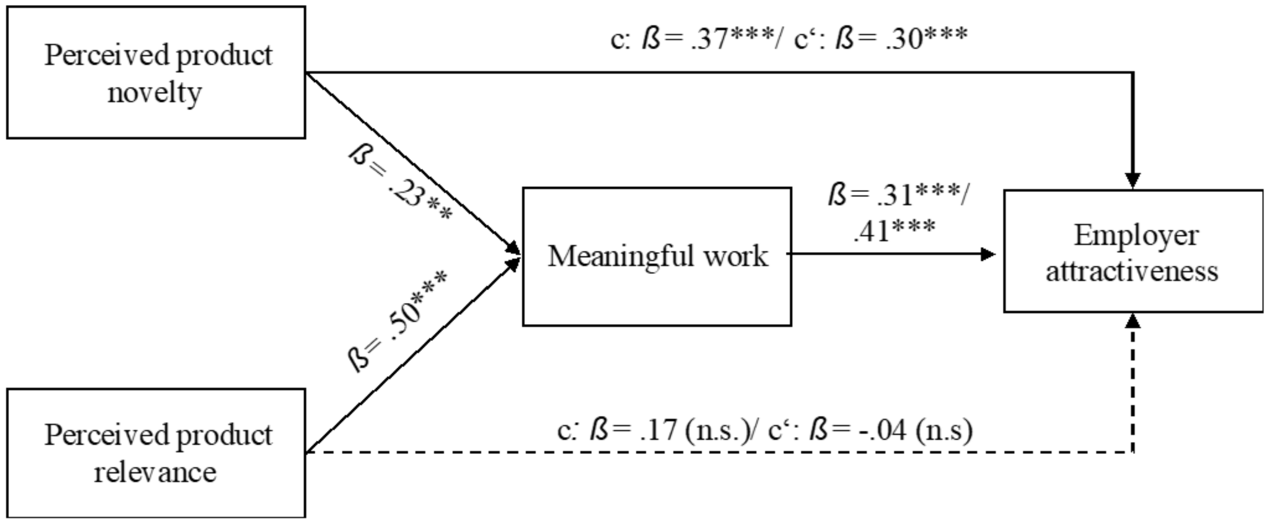

Figure 1: Mediation model – Impact of product-related characteristics on employer attractiveness

Note: Standardized path coefficients are displayed: *** $p < 0.001$; ** $p < 0.01$. Solid lines indicate positive relationships ($p < 0.05$); dashed lines indicate non-significant paths. c indicate the direct relationship (Models 2,3); c' indicate the direct relationships with meaningful work as the mediator (Models 6,7).

attractiveness remained positive ($\beta = .35, p < .001$), whereas perceived product relevance was not significantly related to employer attractiveness ($\beta = .08$, $p = .356$). This joint analysis addresses potential omitted-variable bias and indicates that perceived product novelty exerts a unique effect when controlling for perceived product relevance. Our findings are summarized in Figure 1.

Discussion

This study examined whether perceived product novelty and perceived product relevance relate to employer attractiveness directly and indirectly through meaningful work. The results showed that perceived product novelty was directly and indirectly positively related to employer attractiveness, while perceived product relevance operated only indirectly through meaningful work. In so doing, this study advances research on employer attractiveness in three main ways as well provide practical implications. First, we extend the literature beyond HR-related factors such as compensation, leadership, or work–life balance (e.g., Tanwar and Prasad, 2017; Dabirian et al., 2019) by showing that perceived product novelty and perceived product relevance—dimensions central in branding research (Aaker, 2004)—also matter for how employees evaluate their employer. Prior work has emphasized symbolic attributes for applicants (Lievens and Highhouse, 2003); our results demonstrate that such product-based signals are also relevant for employees, thereby broadening the scope of internal employer branding.

Second, our study also emphasizes the central role of meaningful work in understanding employer attractiveness. Employees who experience their work as meaningful are more likely to report positive attitudes toward their organization, including stronger identification, engagement, and commitment (Pratt and Ashforth, 2003; Rosso et al., 2010; Steger et al., 2012; Bailey et al., 2019; Allan et al., 2019; Lysova et al., 2019). In our model, meaningful work is closely related to both perceived product novelty and perceived product relevance, indicating that employees interpret signals of innovation and societal contribution through their sense of purpose at work. Perceived product novelty positively relates to employer attractiveness both directly and indirectly through meaningful work, whereas perceived product relevance related to attractiveness only indirectly via meaningful work. These findings suggest that employees do not simply respond to organizational products as such but make sense of them in terms of how they shape the meaningfulness of their own work, which in turn is associated with perceptions of their employer's attractiveness.

Third, our study adds empirical evidence from a global B2B chemical company, a context often described as a "dirty industry" that is often associated with environmental concerns and low external appeal (King and Lenox, 2000). By showing that innovation

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and societal contribution in products can strengthen the internal employer brand even under reputational challenges, we provide a critical test case that complements prior studies conducted primarily in consumer-facing or high-reputation industries. This finding suggests that product-related cues may be particularly important in sectors where traditional HR signals alone are insufficient to attract and retain talent.

Limitations and Future Research Directions

As with any single study, our findings should be interpreted in light of certain limitations, which also open avenues for future research. First, we drew on data from one global chemical company. While this provides a critical case for examining employer attractiveness in a sector often associated with reputational challenges, it limits the generalizability of our findings. Future studies should replicate our model across industries with different reputational profiles, such as consumer goods or services, to assess whether the role of perceived product novelty and relevance varies by context (cf. De Waal, 2018; Dabirian et al., 2019).

Second, our analysis was conducted at the individual level, meaning that we examined employees' perceptions rather than objective organizational characteristics. As in prior research on employer attractiveness (Lievens and Highhouse, 2003), this focus captures subjective evaluations that are central to understanding how employees experience their employer. At the same time, future research could complement such studies with multi-company or cross-level designs that compare individual perceptions with organizational-level practices, thereby linking micro- and macro-level insights.

Third, although the fit indices were marginally below conventional thresholds, the hypothesized four-factor model outperformed all alternative specifications and, together with strong convergent validity (factor loadings, CR, AVE) supports the distinctiveness of the constructs. Given the relatively small sample, these findings should be interpreted as indicative of relationships rather than statistical significance, and future studies should replicate the CFA with larger and more diverse samples to further validate structure (Shi et al., 2019). In addition, longitudinal designs with more than two measurement points would allow researchers to examine how perceptions of novelty and relevance evolve in response to product launches, strategic changes, or sustainability initiatives.

Finally, we treated perceptions of product novelty and relevance as stable constructs. However, employees' interpretations are likely dynamic and shaped by organizational and external events. Building on sensemaking theory (Weick, 1995), future research could investigate how critical incidents (e.g., product recalls, breakthrough innovations) shape employees' experience of meaningful work and, in turn, their evaluation of employer attractiveness.

Practical Implications

Our findings provide several actionable insights for organizations seeking to strengthen their internal employer brand. First, for HR managers, the results confirm that symbolic drivers such as perceived novelty and relevance do not substitute traditional HR-related factors. Economic and social value continued to significantly predict attractiveness, underscoring the need for competitive compensation, supportive work environments, and development opportunities. Still, HR can enhance the power of these tangible benefits by complementing them with meaningful narratives about how employees' contributions connect to societal needs through relevant products. In this way, HR integrates "hard" benefits with signals of purpose, thereby reinforcing employees' identification with the organization.

Second, for product development and innovation teams, the finding that perceived product novelty is strongly related to employer attractiveness highlights that innovation is not only a market advantage but also an internal branding asset. Novel products serve as signals of vitality and future orientation (Spence, 2002). Organizations should therefore not only invest in product development but also make these signals visible internally—for example, by communicating innovation milestones, involving employees in product launches, or creating spaces for employees to experience and celebrate innovation. Such practices increase the likelihood that employees interpret novelty as a source of pride and meaningfulness.

Third, for sustainability and CSR functions, our results suggest that the societal relevance of products only translates into employer attractiveness when it is experienced as meaningful. This implies that managers need to actively communicate the broader purpose of products—through sustainability initiatives,

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internal communication campaigns, or opportunities for employees to participate in CSR-related activities. Making societal contributions visible at the job level ensures that relevance is not just an abstract claim but a tangible part of employees' daily work (Aguinis and Glavas, 2019; Glavas and Lysova, 2025). When employees perceive that their work contributes to societal good, signals of product relevance are transformed into meaningful work experiences.

Taken together, these implications suggest that employer branding should be treated as a cross-functional responsibility. HR, innovation, and sustainability managers need to collaborate to align product strategy, societal value creation, and employee experience. Products function as organizational signals that must be supported by HR practices and internal communication, so that employees can interpret them as meaningful. This integrated approach is particularly important in industries such as chemicals, where external reputational challenges make internal branding both more difficult and more essential.

Conclusion

This study advances research on employer attractiveness by shifting the focus from applicants to employees. We show that perceived product novelty relates to employer attractiveness both directly and indirectly via meaningful work, while perceived product relevance relates only indirectly through meaningful work. By integrating branding theory, signalling theory, and meaningful work research, we provide a product- and meaning-based perspective on employer attractiveness. Practically, our findings highlight the importance of aligning product innovation and societal contribution with HR practices to strengthen the internal employer brand. Taken together, our results suggest that employer attractiveness emerges not only from HR-related factors but also from how employees interpret the signals sent by their organization's products.

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Appendix

Table 1. Date Collection Questionnaire

Construct	Item	Scale
Perceived product novelty (PN)	Relative to our main competitors, the products this organization offers in the target market(s): … are radical … are creative … are inventive	1 = strongly disagree 2 = disagree 3 = neither agree nor disagree 4 = agree 5 = strongly agree
Perceived product relevance (PR)	This organizations products: … are useful for society … increase value for society … are relevant for society … serve a purpose for society	1 = strongly disagree 2 = disagree 3 = neither agree nor disagree 4 = agree 5 = strongly agree
Meaningful work (MW)	I have found a meaningful career. I understand how my work contributes to my life's meaning. I have a good sense of what makes my job meaningful. I have discovered work that has a satisfying purpose. I view my work as contributing to my personal growth. My work helps me better understand myself. My work helps me make sense of the world around me. My work really makes no difference to the world. I know my work makes a positive difference in the world. The work I do serves a greater purpose.	1 = strongly disagree 2 = disagree 3 = neither agree nor disagree 4 = agree 5 = strongly agree
Employer attractiveness (EA)	This organization is attractive to me as a place for employment. For me, this organization is a good place to work. I am only working at this organization because I do not have other options. (reverse coded) I like this organization.	1 = strongly disagree 2 = disagree 3 = neither agree nor disagree 4 = agree 5 = strongly agree
Control variables		
Employer attractiveness	How important are the following when choosing an employer? Good relationship with colleagues. (social value) Attractive overall compensation package. (economic value) Feeling more self-confident as a result of working for a particular organization. (development value) Opportunity to teach others what you have learned. (application value)	1 = strongly disagree 2 = disagree 3 = neither agree nor disagree 4 = agree 5 = strongly agree
Gender	What is your gender?	1 = male; 2 = female; 3 = others
Age	What is your age?	Number filled in blank
Job Level	What is your job level?	1 = Junior (1-3 years of experience); 2 = Senior (more than 3 years), currently no direct reports; 3 = Team lead (having direct reports); 4 = Executive
Content of work	What is the content of your work?	1 = administration; 2 = research; 3 = production; 4 = logistics; 5 = other

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Table 2. Descriptive Statistics and Internal Consistency of CFA Items

Construct	*Item*	*M*	*SD*	*Cronbach's α*	*Loading*
Employer attractiveness (EA)	v_608_T2	3.91	0.76	0.865	0.83
	v_609_T2	3.99	0.67	0.865	0.81
	v_610_T2	3.91	0.9	0.865	0.51
	v_611_T2	3.79	0.82	0.865	0.87
Perceived product novelty (PN)	v_554_T1	2.8	0.89	0.708	0.37
	v_555_T1	3.51	0.81	0.708	0.81
	v_557_T1	3.64	0.8	0.708	0.90
Perceived product relevance (PR)	v_570_T1	3.96	0.78	0.93	0.87
	v_571_T1	3.84	0.74	0.93	0.88
	v_572_T1	3.84	0.77	0.93	0.88
	v_573_T1	3.9	0.77	0.93	0.88
Meaningful work (MW)	v_635_T2	3.78	0.7	0.907	0.62
	v_636_T2	3.58	0.82	0.907	0.71
	v_637_T2	3.89	0.68	0.907	0.70
	v_638_T2	3.72	0.72	0.907	0.76
	v_639_T2	3.8	0.78	0.907	0.71
	v_640_T2	3.22	0.96	0.907	0.65
	v_641_T2	2.98	0.92	0.907	0.74
	v_642_T2	3.3	0.88	0.907	0.74
	v_643_T2	3.17	0.95	0.907	0.77
	v_644_T2	2.97	1.02	0.907	0.69

Note: n = 138

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Table 3. Descriptive Statistics

		M	*SD*	*Min.*	*Max.*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
1.	Employer attractiveness	3.89	0.63	1.8	5.0	(.90)**α**											
2.	Perceived product novelty	3.32	0.66	1.0	5.0	0.42**	(.71)**α**										
3.	Perceived product relevance	3.89	0.69	2.0	5.0	0.23**	0.23**	(.93)**α**									
4.	Meaningful work	3.89	0.63	1.7	4.9	0.36**	0.25**	0.57**	(.92)**α**								
Control Variables																	
5.	Social Value	4.30	0.58	3.0	5.0	0.26**	0.11	0.04	0.07	1							
6.	Economic value	4.29	0.68	2.0	5.0	0.26**	0.08	-0.06	0.01	0.19*	1						
7.	Development value	3.80	0.81	1.0	5.0	0.23**	0.24**	0.17*	0.31**	0.26**	0.20*	1					
8.	Application value	4.05	0.77	1.0	5.0	0.10	-0.01	0.03	0.15	0.23**	0.13	0.31**	1				
9.	Age	39.33	7.82	21.0	52.0	-0.08	-0.11	0.01	0.11	-0.17*	-0.04	-0.07	-0.06	1			
10.	Gender	1.38	0.49	1.0	2.0	0.13	0.18*	-0.03	0.02	-0.07	-0.02	0.15	0.05	-0.19*	1		
11.	Job level	2.20	0.70	1.0	4.0	-0.06	-0.14	0.26**	0.30**	-0.10	0.05	0.01	0.19*	0.43**	-0.23**	1	
12.	Functional area	3.52	1.55	1.0	5.0	0.00	-0.03	-0.06	0.06	-0.07	-0.16	0.09	-0.05	0.11	-0.14	0.03	1

Note: n = 138

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

α Cronbach's alpha reliability coefficient on diagonal.

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Table 4. Confirmatory Factor Analysis: Model Fit Comparison

Model	*χ²(df)*	*CFI*	*TLI*	*RMSEA [90% CI]*	*SRMR*	*AIC*	*BIC*
1-Factor	1146.959 (209)	0.624	0.608	0.152 [.142, .163]	0.101	6424.351	6553.150
2-Factor (Products | MW+EA)	871.789 (208)	0.747	0.728	0.125 [.116, .134]	0.090	6159.100	6283.826
3-Factor (Products = PR+PN)	589.139 (206)	0.821	0.800	0.116 [.105, .126]	0.080	5996.720	6130.720
4-Factor (Hypothesized)	431.858 (203)	0.878	0.862	0.090 [.079, .102]	0.080	5722.159	5868.522
4-Factor (no v_554_T1)	412.762 (183)	0.877	0.869	0.095 [.081, .108]	0.081	5377.765	5518.273

Note: n = 138, Standardized estimates. The hypothesized four-factor model provided the best fit relative to all alternatives.

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Table 5. Regression Models

		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Interdependent variables		Control	Controls Perceived product novelty	Controls Perceived product relevance	Controls Perceived product novelty	Controls Perceived product relevance	Controls Perceived product novelty	Controls Perceived product relevance	Controls Perceived product novelty Perceived product relevance
Mediator variables							Meaningful work	Meaningful work	
Dependent variables		Employer attractiveness	Employer attractiveness	Employer attractiveness	Meaningful work	Meaningful work	Employer attractiveness	Employer attractiveness	Employer attractiveness
		Beta values	***Beta values***	***Beta values***	***Beta values***	***Beta values***	***Beta values***	***Beta values***	***Beta values***
Controls	Social value	0.20*	0.18*	0.20*	0.03	0.02	0.17*	0.19*	0.18*
	Economic value	0.22*	0.21*	0.24**	-0.08	-0.00	0.23**	0.24**	0.22**
	Development value	0.11	0.03	0.07	0.25**	0.19	-0.05	-0.01	0.01
	Application value	-0.01	0.03	0.01	0.02	0.04	0.02	-0.01	0.03
	Age	0.00	0.01	0.02	0.02	0.07	0.00	-0.01	0.02
	Gender	0.14	0.09	0.14	0.02	0.06	0.09	0.12	0.10
	Job level	-0.02	0.01	-0.07	0.33***	0.14	-0.09	-0.13	-0.02
	Functional area	0.06	0.07	0.08	0.03	0.08	0.06	0.04	0.08
Main effect	Perceived product novelty		0.37***		0.23**		0.30***		0.35***
	Perceived product relevance			0.17		0.50***		-0.04	0.08
	Meaningful work						0.31***	0.41***	
Mediating effects (bootstrapping)	Meaningful work						0.07*	0.20*	
	R^2	0.15**	0.28***	0.18**	0.24***	0.41***	0.35***	0.28***	0.28***
	Adjusted R2	0.10**	0.22***	0.12**	0.19***	0.37***			0.22***
	F	2.92**	5.39***	3.05**	4.48***	9.80***	6.76***	4.81***	4.93***

Note: n = 138; Standard coefficients are reported; *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$;
Significance based on 95% bootstrapped confidence intervals (PROCESS Model 4).

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Table 6. Mediating effects (Hays Process Model)

Path	ß	p - value	95% CI
	Model 6 (IV = Perceived product novelty)		
Perceived product novelty - Meaningful work (a1)	0.23	0.005	[0.069, 0.373]
Meaningful work - Employer attractiveness (b1)	0.31	< 0.001	[0.148, 0.477]
Direct effect perceived product novelty - Employer attractiveness (c’)	0.37	< 0.001	[0.202, 0.502]
Indirect effect (a1 x b1, bootstr.)	0.07	-	[0.013, 0.152]
	Model 7 (IV = Perceived product relevance)		
Perceived product relevance - Meaningful work (a2)	0.50	< 0.001	[0.323, 0.585]
Meaningful work - Employer attractiveness (b2)	0.41	< 0.001	[0.215, 0.608]
Direct effect perceived product relevance - Employer attractiveness (c’)	0.17	0.059	[-0.006, 0.307]
Indirect effect (a2 x b2, bootstr.)	0.20	-	[0.074, 0.370]

Note: n = 138; Standard coefficients are reported; IV = independent variable
Significance based on 95% bootstrapped confidence intervals (PROCESS Model 4).

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Research Paper

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Sustainable Use of PiWi Vine Leaves: Life Cycle Assessment and Techno-Economic Analysis of a Novel Vine-Leaf-Based Beverage within the Framework of the Circular Bioeconomy

This study investigates the ecological and economic performance of a novel, alcohol-free beverage derived from the leaves of fungus-resistant (PiWi) grapevines as part of a research project funded by the Federal Ministry of Research, Technology and Space. Using life cycle assessment (LCA) and techno-economic analysis (TEA), the study evaluates both the environmental footprint and the production costs of the beverage across multiple production scenarios. The results indicate that the PiWi-based beverage shows clear ecological advantages compared to already available drinks such as tea-based beverages, fermented lemonades, and alcohol-free wine, mainly due to lower pesticide use and energy demand. Economically, production is feasible within competitive cost ranges, especially when existing winery infrastructure is utilized.

Keywords: BioBall, Vine leaves, Capital expenditure (CAPEX), Bioeconomic, Earnings before interest and taxes (EBIT), Earnings before interest, tax, depreciation, and amortization (EBITDA), Operational expenditure (OPEX), Return on investment (RoI), Techno-economic assessment (TEA), Life cycle assessment (LCA), Fungus-resistant grapevines (PiWi), Climate change, Circular economy

Introduction

In recent years, societal and political awareness of climate change and its associated risks have increased significantly (Calculli et al., 2021). This development is reflected in numerous national and international agreements and strategies aimed at curbing climate change and promoting sustainable transformation processes. A central milestone in this regard was the Paris Climate Agreement of 2015, in which the international community agreed to limit global warming to well below 2 °C, ideally to 1.5 °C, compared to pre-industrial levels (Vertragsparteien: Übereinkommen von Paris, 2015). In the same year, the 2030 Agenda with its 17 Sustainable Development Goals (SDGs) was adopted. Particularly relevant for agriculture and climate protection are SDG 2 ("Zero Hunger" – including sustainable agriculture), SDG 12 (sustainable consumption and production), and SDG 13 (climate action) (Bundesministerium für Wirtschaftliche Zusammenarbeit und Entwicklung: Die Agenda 2030 für nachhaltige Entwicklung, n.d.).

At the European level, the European Green Deal (2020) set out a comprehensive strategy that includes the objective of reducing the EU's net greenhouse gas emissions to zero by 2050. As part of this, the "Fit for 55" package was

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initiated, which aims to reduce emissions by at least 55% by 2030 compared to 1990 levels. Other central elements include the 2030 Biodiversity Strategy, the Circular Economy Action Plan (Europäische Kommission: Der europäische Grüne Deal, 2021), and the "Farm to Fork" strategy, which calls for, among other things, a 50% reduction in pesticide use and at least a 20% reduction in fertilizer use by 2030 (Food Safety: Farm to Fork Strategy, n.d.). To achieve these far-reaching goals, new concepts are required that combine ecological sustainability with economic innovation. The bioeconomy plays a significant role here, as it represents a forward-looking approach to using biological resources efficiently and sustainably.

The bioeconomy is defined by the Federal Ministry of Research, Technology and Space as "the production, exploitation, and utilization of biological resources, processes, and systems in order to provide products, processes, and services across all economic sectors within a future-oriented economic system" (Federal Ministry of Research, Technology and Space – BMFTR, 2025). Complementarily, Muscat et al. define the circular bioeconomy as a strategy intended to "minimize the consumption of finite resources (e.g., phosphate rock, fossil fuels, or soils), promote regenerative practices (e.g., restoration of fish stocks), prevent the loss of natural resources (e.g., carbon, nutrients, and water), and foster the reuse and recycling of unavoidable by-products, losses, or waste in a way that maximizes added value for the system" (Muscat et al., 2021).

Within this context, the present research project focuses on the use of vine leaves, a raw material that has so far remained unused, thereby providing an ideal example of sustainable utilization concepts. Currently, vine leaves are traditionally preserved in the Mediterranean region through lactic acid fermentation for dishes such as dolmades (Ünver et al., 2007), while in Asia they are mainly consumed as teas (Rana et al., 2022). Beyond their culinary use, vine leaves rank among the most common by-products of viticulture (Maia et al., 2021). Their high content of bioactive compounds, particularly phenolic substances and organic acids, offers not only nutritional benefits but also considerable economic potential (Constantin et al., 2024). Building on this potential, the project seeks to develop an innovative beverage that makes targeted use of these valuable ingredients. In doing so, it not only illustrates the possibility of converting by-products of viticulture into high-quality foods but also serves as a model for sustainable production processes in the wine sector.

These overarching goals and concepts place agriculture, and viticulture in particular, under considerable pressure to transform. Grapevines are considered one of the most pesticide-intensive crops (Chen et al., 2022), as they are highly susceptible to fungal diseases such as powdery and downy mildew (Vella et al., 2024). According to the Pesticide Action Network Europe (2008), vineyards account for only about 3.5% of agricultural land but consume around 15% of the synthetic pesticides used in the EU. A key strategy for reducing pesticide use, according to the German Environment Agency, lies in the increased use of robust plant varieties (Merbold, 2016). In viticulture, this means specifically promoting so-called fungus-resistant grapevine varieties (abbreviated PiWi, from the German pilzwiderstandsfähig, or FRW – fungicide-resistant grapevines). These cultivars exhibit genetic resistance, particularly to mildew diseases, and therefore require significantly fewer plant protection measures. Studies show that pesticide use in PiWi varieties can be reduced by up to 80% compared to conventional grapevine varieties (Dressler, 2024; Pedneault & Provost, 2016).

In addition to ecological benefits, reduced pesticide use is also associated with economic and social advantages. According to recent studies, production costs per hectare can be reduced by 46% to 75% (Dressler, 2024). Moreover, the health risks for vineyard workers are minimized due to reduced exposure to pesticides, which in turn has positive effects on working conditions and work-life balance.

Thus, PiWi grape varieties promote all three dimensions of sustainability (Federal Ministry of Research, Technology and Space – BMFTR, 2025):

- Ecological, through reduced pesticide use and the protection of biodiversity,
- Economic, through lower production costs, and
- Social, through improved working conditions.

Despite these potentials, PiWi varieties currently account for only about 3.5% of the total vine-yard area in Germany (Deutsches Weininstitut, 2025). According

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to Duley et al. (2022), barriers include low market acceptance and necessary adjustments in oenological processing due to the differing chemical composition of the grapes (e.g., altered aroma and acid profile) (Duley et al., 2023). Beyond the use of grapes, however, PiWi grapevines offer an underexplored potential for valorisation: their leaves. Considering the challenges associated with grape processing, vine leaves provide an alternative path to value creation that not only contributes to better use of the plant but also enables new, innovative product approaches.

Against this background, the research project funded by the BMFTR aims to develop a novel, predominantly alcohol-free beverage produced specifically from the leaves of fungus-resistant grapevines. The goals are to promote the acceptance of PiWi grapevines, open up new value-creation perspectives, and simultaneously contribute to the circular bioeconomy. Since these leaves contain particularly low levels of pesticide residues due to the reduced need for spraying, they are ideally suited for sustainable utilization. The aim is to generate a high-value product from a previously unused by-product, thereby creating a tangible example of circular bioeconomy in viticulture.

To assess the sustainability and economic viability of the research project, a life cycle assessment (LCA) as well as a techno-economic analysis (TEA) are conducted. The LCA is also recommended by the European Commission (Europäische Kommission, 2003; Europäische Union, 2013) and is a standardized method according to ISO norms 14040 (Deutsche Norm, 2009) and 14044 (Deutsche Norm, 2006) for evaluating environmental performance along the life cycle. The objective of this study is to assess the environmental impact of a beverage made from PiWi vine leaves and to conduct a comparative LCA. In this study, a “cradle-to-gate” approach is chosen, whereby the distribution and use phases are not considered due to uncertainties (Benedetto, 2013). Based on the LCA data, the project is also examined from an economic perspective to analyse the potential additional benefits for wine-growers.

Methods

Life Cycle Assessment

The investigated beverage can be categorized as a fermented lemonade, as it is produced from vine leaves that are first extracted and subsequently fermented. Fermented lemonades are characterized by the conversion of plant-based sugars or extracts through microbial fermentation, resulting in a mildly acidic and non-alcoholic beverage (Jenny, 2019). To ensure a comprehensive assessment within a broader spectrum of fermented and non-alcoholic beverages, it is additionally compared with products from related categories. This approach allows for evaluating its environmental performance not only within its own class but also relative to established reference products.

The environmental impacts of the beverage are assessed through a life cycle analysis using the software openLCA and the databases Ecoinvent v.3.10 (FitzGerald et al., 2024) and, where datasets are missing, Agribalyse. The methodological framework is based on the CML 2016 method (Guinee, 2002). The foreground data required for the inventory are primarily provided by project partners or taken from scientific literature.

The objective of the study is to quantify the potential environmental impacts of producing one liter of the newly developed beverage based on PiWi vine leaves and to identify ecological hotspots along the value chain. In addition, five alternative production scenarios are analysed to evaluate the effects of different design options:

- **Scenario 1**: German electricity mix and glass bottle packaging (DSM+G)
- **Scenario 2**: Renewable energy sources and glass bottle packaging (RE+G)
- **Scenario 3**: PET bottles with the German electricity mix (DSM+PET)
- **Scenario 4**: Renewable energy sources and PET bottles (RE+PET)
- **Scenario 5**: Conversion to organic viticulture with glass bottle packaging and German electricity mix (Organic)

Furthermore, a comparison with existing beverages is conducted: a fermented lemonade, a tea-based beverage, and an alcohol-free wine produced by vacuum distillation. The selection of these comparative products follows the criteria “alcohol-free” and “comparable product category.” The process for the fermented lemonade is fully modelled using literature data (Nachhaltigkeitsbericht 2022/23, 2023; De Marco et al.,

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2016.) For the tea-based beverage, partly manufacturer-specific primary data are used and complemented with literature data (Azapagic et al., 2015, Xu et al., 2019). For alcohol-free wine, existing wine production data are combined with a vacuum distillation process simulated in Aspen V.11.

Functional Unit and System Boundary

The functional unit (FU) is defined in all scenarios and comparative processes as one liter of beverage in a ready-to-sell container.

The system boundaries include all relevant processes, from the agricultural production of vine leaves through processing, fermentation, bottling, and packaging, up to the delivery of the final product at the "factory gate." It is assumed that an already established vineyard exists, which only requires mulching, fertilizing, and spraying (see Fig. 1). The use and end-of-life phases (e.g., cooling, consumption, packaging recycling) are excluded, as no reliable data are available at the time of analysis. Their inclusion would have led to high uncertainty, which is also confirmed by the literature (Bendetto, 2013, Borsato et al., 2019). According to Casolani et al., 33% of the reviewed studies are limited to a cradle-to-gate approach (Casolani et al., 2022).

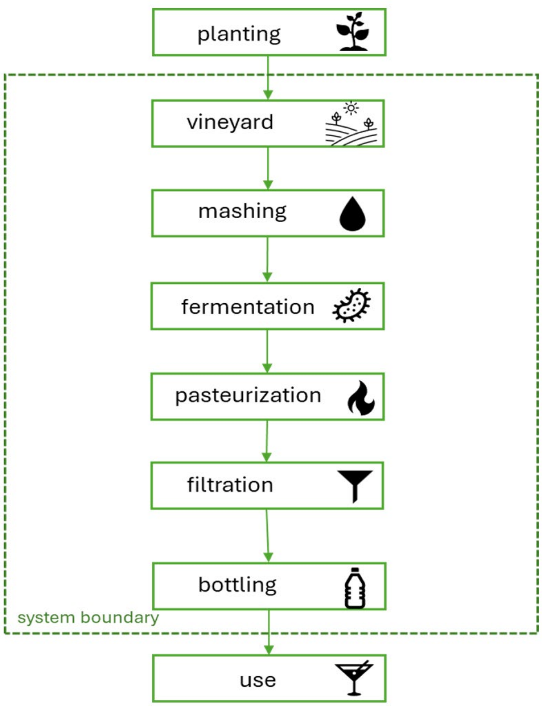

Figure 1. Visualization of the system boundary

Data Collection and Assumptions

The necessary data for all process stages are collected by project partners during the 2023/2024 survey period. Additionally, literature values are used where required, for example for the bottling process (see Appendix).

Agricultural production is based on an existing vineyard that is regularly mulched, fertilized, and treated with pesticides. Transport distances between vineyard, winer, and bottling facility are considered negligible. Leaf pressing results in a 5% liquid loss, while overall process-related liquid losses amount to about 36%, as measured. The product is filtered analogously to wine. Biogenic emissions from fermentation and leaf residues are not included.

To accurately quantify these process flows, the foreground data encompass quantities of fertilizers, sugar, and other input materials, leaf and grape yields per hectare, the amount of ex-tracted and fermentated produced, process losses, as well as the consumption of diesel, water, and electricity. Background data, such as the production and disposal of used inputs and fuels, are represented through appropriate databases.

The use of agricultural machinery is also modelled via background processes, which account for both direct emissions from diesel combustion and the proportional production, maintenance, and disposal of the machines. A separate modelling of these machines within the primary process is not carried out. The same applies to building infrastructures: the construction and maintenance of agricultural buildings and winery facilities are not explicitly modelled but are included in background data.

For the vineyard process step, allocation by volume is applied since both vine leaves and grapes are produced. The allocation of environmental impacts is based on the number of liters of wine and beverage that can be obtained from one hectare of vineyard. This volumetric method is chosen because it reflects the realistic ratio between main and co-products. For packaging, recycled content is considered: glass bottles contain approximately 66% cullet (Wilke, 2024), and PET bottles consist of about 52% recycled material (Schmidt, 2024).

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Techno-Economic Analysis

A techno-economic analysis is conducted to assess the economic performance of the developed product. The goal is to determine the production costs of the beverage, perform a static profitability analysis, and identify the main cost drivers along the process chain. The methodological approach follows Activity-Based Costing (ABC), as this method has proven suitable in earlier viticulture studies (González-Gómez & Morini, 2006, Mura et al., 2022b).

The system boundaries of the TEA are consistent with the life cycle analysis (cradle-to-gate), i.e., the analysis considers all production steps from vineyard to delivery of the final product at the factory gate.

The costs of machinery, equipment, and buildings are calculated using the KTBL dataset Viticulture and Winery – Data for Farm Planning (Becker et al., 2017b). Standard values and assumptions provided there are adopted. Both fixed costs (e.g., depreciation, insurance, storage, interest on tied capital) and variable costs are determined per process step based on process duration. For investments and machinery used in both grape and leaf processing, allocation by volume is applied to ensure a fair distribution of costs. This allocation method is used consistently across all relevant process steps. Only in the vineyard stage are operating resources and consumables also allocated.

Personnel costs are calculated based on the working time per task. The basis is a weighted average hourly wage, derived from the statutory minimum wage for seasonal workers (€12.82/h) and the wage for permanent employees (€17.50/h). Assuming that 15% of the workforce are seasonal workers, the weighted average wage is €16.77/h (Becker et al., 2017).

Two scenarios are modelled:

Scenario 1 – Greenfield: assumes full new investments in all machinery, equipment, and buildings. In addition to depreciation, ongoing fixed costs such as insurance premiums, storage, and interest on tied capital are included. The vineyard itself is considered already established.

Scenario 2 – Brownfield: assumes that all capital goods (machinery, buildings, etc.) are already available and fully depreciated. In this case, fixed costs are limited to maintenance, storage, insurance, and technical monitoring.

Results and Discussion

Life Cycle Assessment

In selecting appropriate impact categories, this study follows Ferrara et al. (2018), who identifies the environmental indicators most frequently applied in the literature. Accordingly, the carbon footprint (CF), acidification potential (AP), and eutrophication potential (EP) are considered the central indicators within the wine sector.

The carbon footprint captures the impacts on climate change and is particularly relevant, as it is one of the most used indicators in life cycle assessments (Bendetto, 2013). The acidification potential considers the effects of acidifying substances, which can affect soils, groundwater and surface water, organisms, ecosystems, as well as materials such as buildings. This category is significant in viticulture, as the use of diesel, fertilizers, and other chemicals leads to corresponding emissions. The eutrophication potential assesses the effects of excessive macronutrient inputs on environmental compartments such as air, water, and soil, which arise from the use of fertilizers and pesticides. In addition, the terrestrial ecotoxicity potential (TETP) is analysed separately. It describes the potential harm to soil organisms from toxic substances released during the production pro-cess, particularly from pesticides, herbicides, fungicides, and other agrochemicals (Guinee, 2002; Azapagic et al., 2015). This category is especially relevant in viticulture, as vineyards are intensively managed and the use of such substances is common. Considering TETP therefore enables an assessment of impacts on soil biology and long-term soil fertility.

For the impact assessment, the CML method is applied a midpoint-oriented methodology developed at the Centrum voor Milieukunde of Leiden University (Guinee, 2002). This method is widely used in the wine sector because it directly relates to the typical inputs in vineyards, thereby ensuring both plausibility and comparability with other studies (Ferrara & De Feo, 2018). Figures 2 to 5 illustrate the results of the impact

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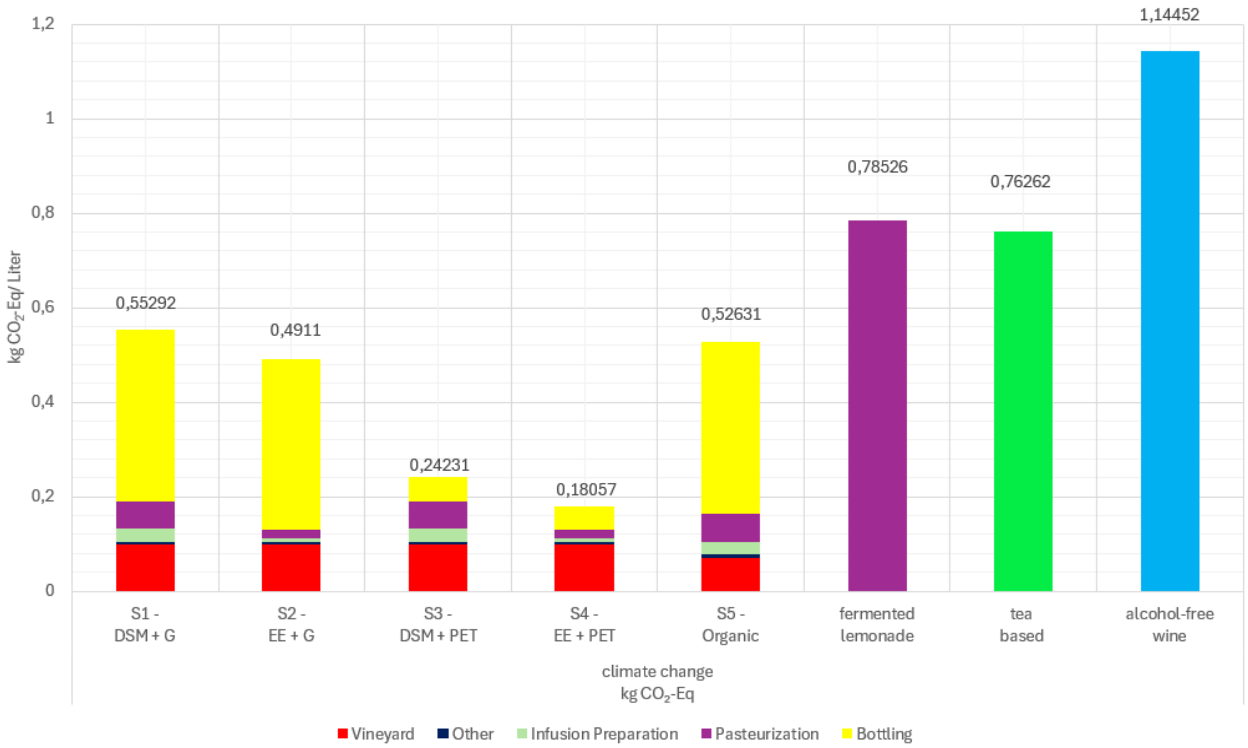

Figure 2 Comparison of Climate Change Results

assessment for the selected environmental categories, showing both the contributions of individual process steps to the overall impacts and the comparison between the investigated scenarios and reference processes.

The comparison of Scenarios 1–5 with the reference processes in the aggregated impact category of climate change shows that all scenarios remain below the CO_2-equivalents of the reference products. In Scenarios 1, 2, and 5, bottling represents the largest contribution to climate impact, with energy-intensive glass production accounting for 99% of the environmental effects in this process stage. By substituting glass with PET, Scenario 3 achieves a reduc-tion of approximately 56.2% in CO_2-equivalents compared to Scenario 1; however, this effect is strongly dependent on the chosen system boundaries. When additional life cycle phases such as distribution and disposal are included, the differences between glass and PET bottles diminish, particularly in the case of reusable glass (Ferrara et al., 2021).

Another significant contribution to climate impact arises in the vineyard process, primarily due to diesel consumption and related emissions, a finding that has already been confirmed in numerous wine LCA studies (Fusi et al., 2013; Benedetto, 2013; Navarro et al., 2016). In Scenario 5, the reduced pesticide uses leads to fewer tractor operations and thus to lower environmental burdens in the vineyard. The use of renewable electricity in Scenarios 2 and 4 reduces CO_2-equivalents by 0.06 kg, primarily in the cellar processes of pasteurization and infusion. This finding is also reflected in previous studies (Navarro et al., 2016; Fusi et al., 2013).

For the reference processes, a more differentiated picture emerges in the fermented lemonade, the largest share of emissions originates from glass production (45%), followed by malt production (28%). In the tea-based beverage, glass production likewise dominates (47%), while electricity generation accounts for the second-largest share at 36%. For alcohol-free wine, by contrast, 56% of CO_2 emissions result from electricity generation. Overall, the five PiWi beverage scenarios perform best in the climate change impact category and consistently Terrestrial ecotoxicity describes the potential toxic effects of chemicals such as as pesticides and fertilizers on terrestrial ecosystems and uses p-dichlorobenzene (DCB) as the reference substance (Gemeinsame Forschungsstelle: Institut für Umwelt und Nachhaltigkeit, 2010). In Scenarios 1–4, the vineyard process is the dominant factor, contributing approximately 90% of the total environmental impact. The primary cause is

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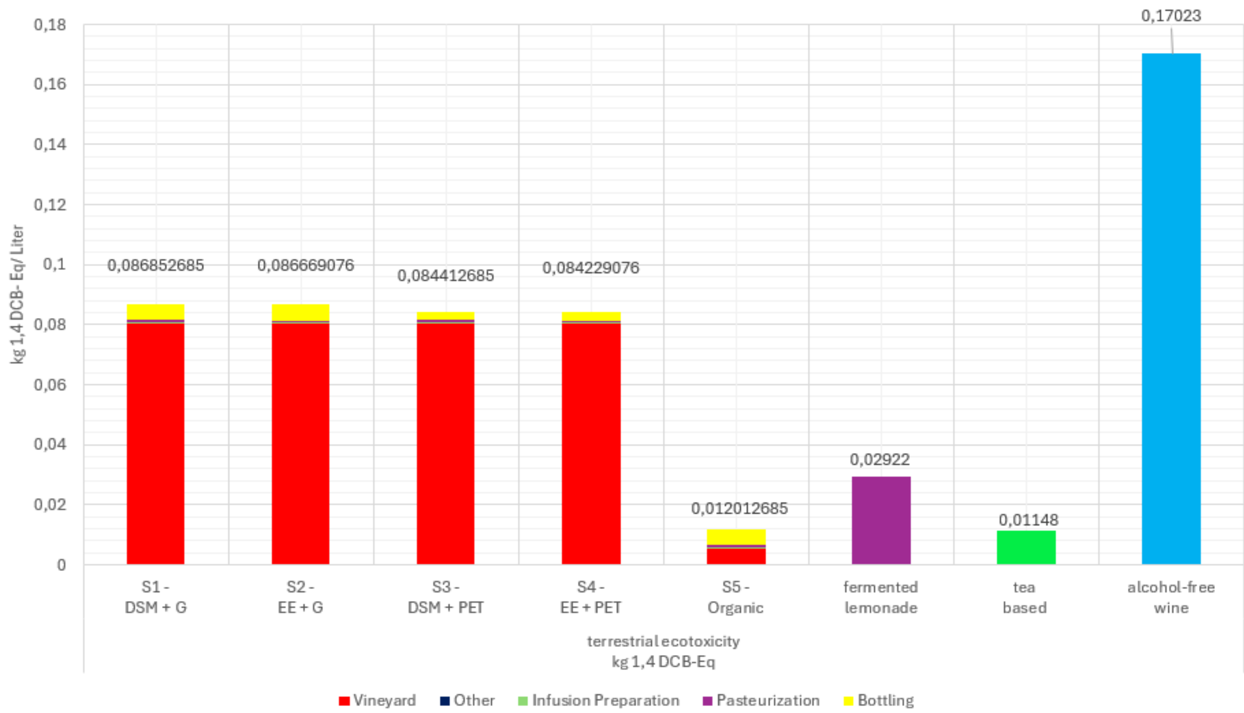

Figure 3 Comparison of Terrestrial Ecotoxicity Results

the direct emissions resulting from the application of fertilizers and plant protection products. Under organic viticulture, terrestrial ecotoxicity can be reduced by about 86.2% (in kg 1,4-DCB equivalents) due to the substan-tially lower use of synthetic pesticides.

In the case of the reference processes, 61% of the 1,4-DCB equivalents for the fermented lemonade originate from malt production. For the tea-based beverage, glass production dominates with a share of 45%, while in alcohol-free wine, direct emissions account for the largest contribution at 89%.

A comparison with the results of a systematic review of wine life cycle assessments shows that the present results, except for alcohol-free wine, fall within the lower range of values reported for terrestrial ecotoxicity. The review reports a range of 0.013 to 0.93 kg 1,4-DCB eq. per liter of wine. As confirmed in the present analysis, the findings of Jourdaine et al. indicate that the level of terrestrial ecotoxicity strongly depends on the amount and type of pesticide applied. This relationship explains the large variability observed in the reported values (Jourdaine et al., 2019).

Acidification potential primarily results from emissions of nitrogen oxides, sulfur dioxide, and ammonia (Gemeinsame Forschungsstelle: Institut für Umwelt und Nachhaltigkeit, 2010). Similar to the category „climate change," bottling is the dominant contributor, with glass production playing a decisive role in particular. In the vineyard, diesel consumption and pesticide production significantly contribute to acidification.

For the fermented lemonade, the largest share of SO_2 equivalents stems from malt production (38%). For the tea-based beverage, glass production dominates with 52%, whereas in alcohol-free wine, electricity generation accounts for the highest contribution (42%).

Compared to the reference products, the PiWi beverage shows the lowest environmental impacts in the impact category acidification potential. Overall, the results are in line with previous wine LCAs. The reported values range from 0.027 kg SO_2 equivalents per liter of wine (Point et al., 2012), 0.016 kg SO_2 equivalents per liter of wine (Benedetto, 2013), down to 0.00209 kg SO_2 equivalents per liter of wine (García et al., 2023).

Eutrophication is primarily caused by emissions of nitrogen and phosphorus compounds (Joint Research Centre: Institute for Environment and Sustainability, 2010). Across the five scenarios under study, the overall impacts differ only slightly. This is mainly due to

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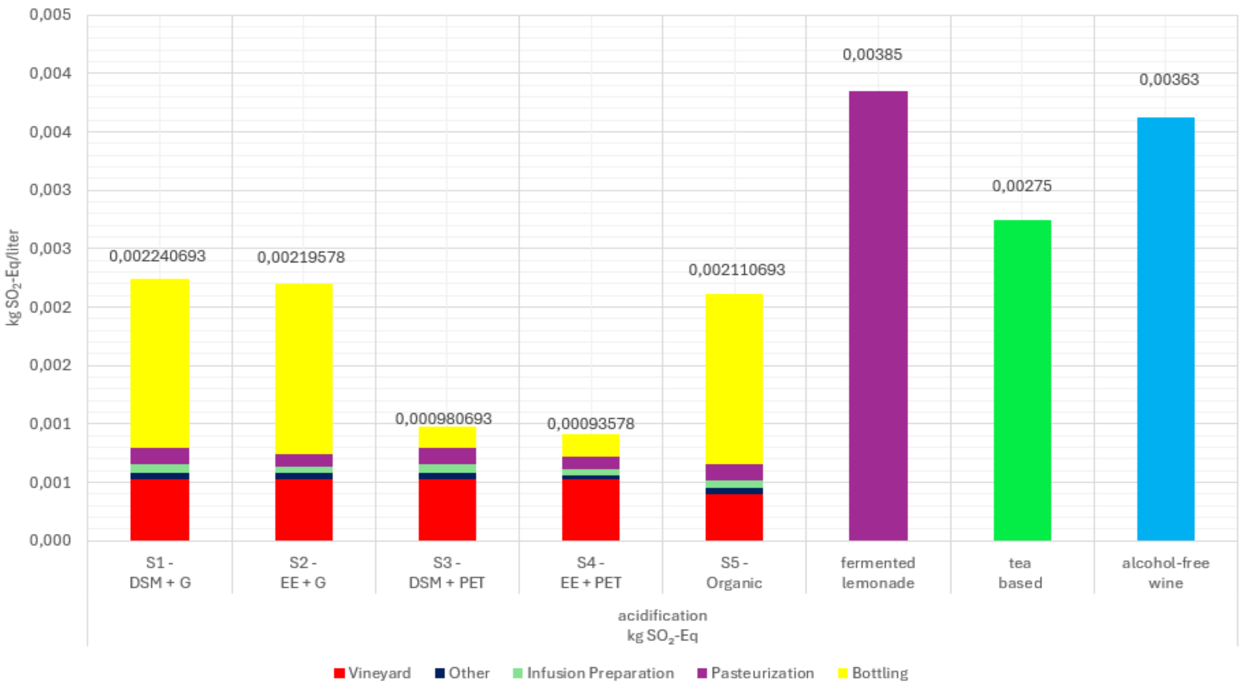

Figure 4 Comparison of Acidification Potential Results

process-specific factors: in bottling with glass containers, polyethylene film used for transport contributes notably to the burden, whereas in PET packaging, the production of terephthalic acid plays a significan role. In the vineyard, the largest share results from the direct emissions of fertilizers and pesticides.

For the reference processes, most PO_4-equivalents in the fermented lemonade stem from malt production (52%). In the tea-based beverage and alcohol-free wine, electricity generation dominates, accounting for 45% and 56%, respectively.

A comparison of the PiWi beverage and the reference processes with published wine LCAs shows that, except for alcohol-free wine, these results fall mostly at the lower end of the reported range. For instance, Benedetto et al. determine a eutrophication potential of 0.002 kg PO_4 eq per liter of wine (Benedetto, 2013), whereas Point et al. report a significantly higher value of 0.0081 kg PO_4 eq per liter of wine (Point et al., 2012).

The analysis shows that the innovative leaf-based beverage demonstrates a significantly better environmental performance in almost all investigated scenarios compared to the selected reference products – non-alcoholic beer, tea-based beverage, and non-alcoholic wine. In contrast to the reference products, where the largest environmental impacts stem from energy-intensive processes such as tea production, malt production, or vacuum rectification, the PiWi beverages benefit from several key factors. On the one hand, the use of PiWi vines significantly reduces pesticide application, which also lowers diesel consumption for plant protection measures, and the production itself is comparatively low in electricity consumption, avoiding further emissions.

The scenario analysis illustrates how different design options influence environmental impacts. Although the use of renewable energy has a relatively minor effect overall, it can none-theless relieve cellar processes in particular. Under organic cultivation (Scenario 5), terrestrial ecotoxicity and other agriculture-related impacts are reduced most substantially. Overall, it becomes evident that the combination of PiWi vines, sustainable energy supply, and organic viticulture markedly improves the beverage's environmental performance across all categories.

Techno-Economic Analysis

For the evaluation of the techno-economic analysis, a cost structure analysis is first conducted to identify the main cost drivers in each scenario.

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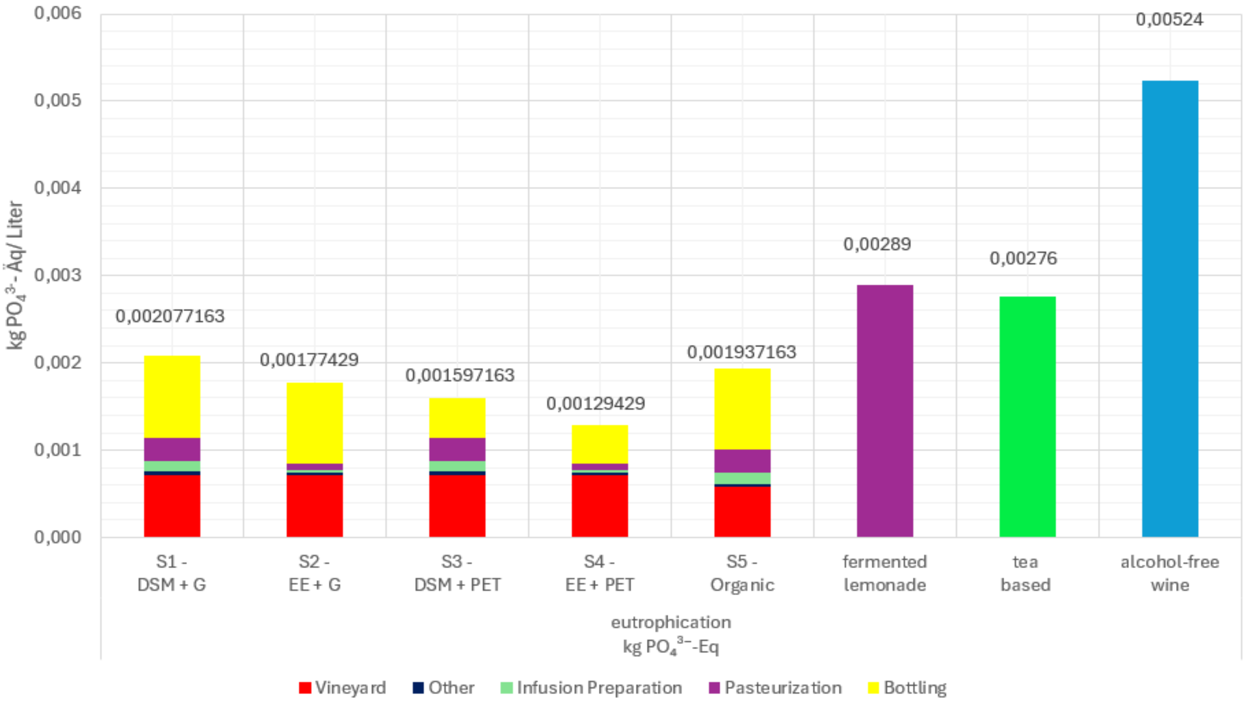

Figure 5 Comparison of Eutrophication Results

In the Brownfield scenario, depreciation is entirely eliminated, which removes the previously dominant cost driver in the vineyard process step (-€0.35 per liter). In the overall cost structure, this leads to a relative shift: variable costs now account for 94.9%, forming the almost sole cost component, while fixed costs make up only 5.1% (cf. Fig. 7). For the cellar operations and bottling process steps, however, no significant changes occur. In the Greenfield scenario (Scenario 1), variable costs dominate, accounting for 82.53% of the total production costs, followed by depreciation (13%) and fixed costs (4.5%). A detailed examination of the individual process

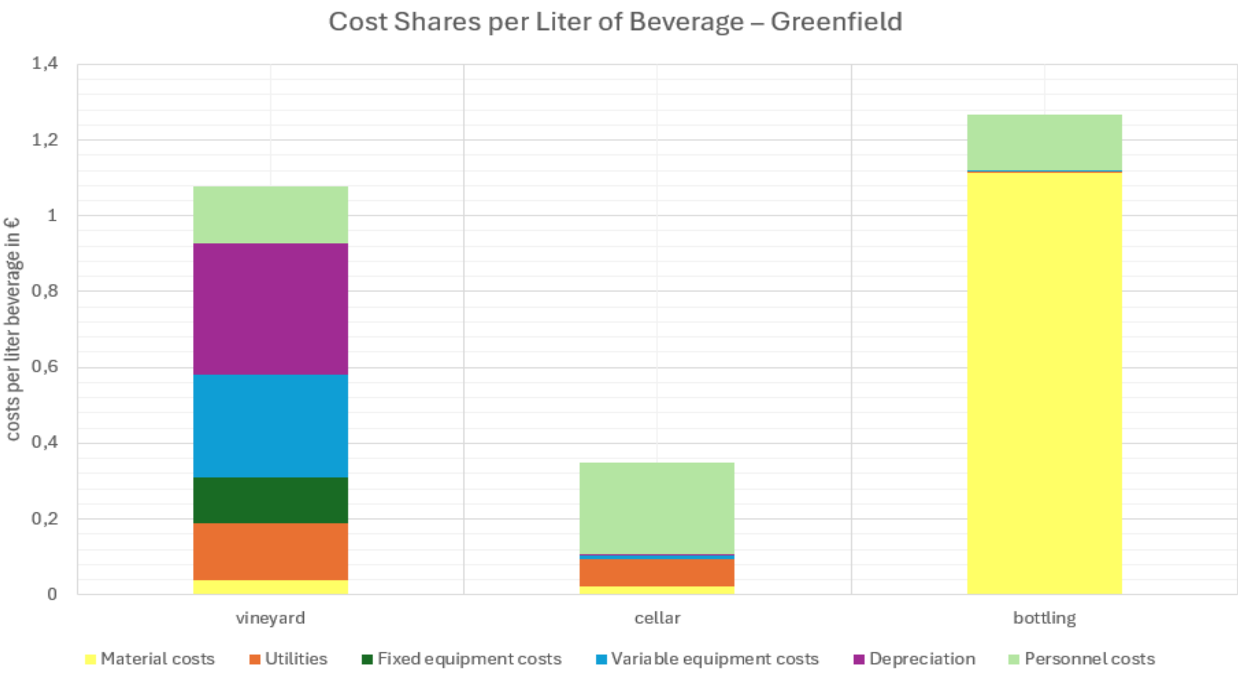

Figure 6 Share of costs per liter of beverage in the greenfield scenario

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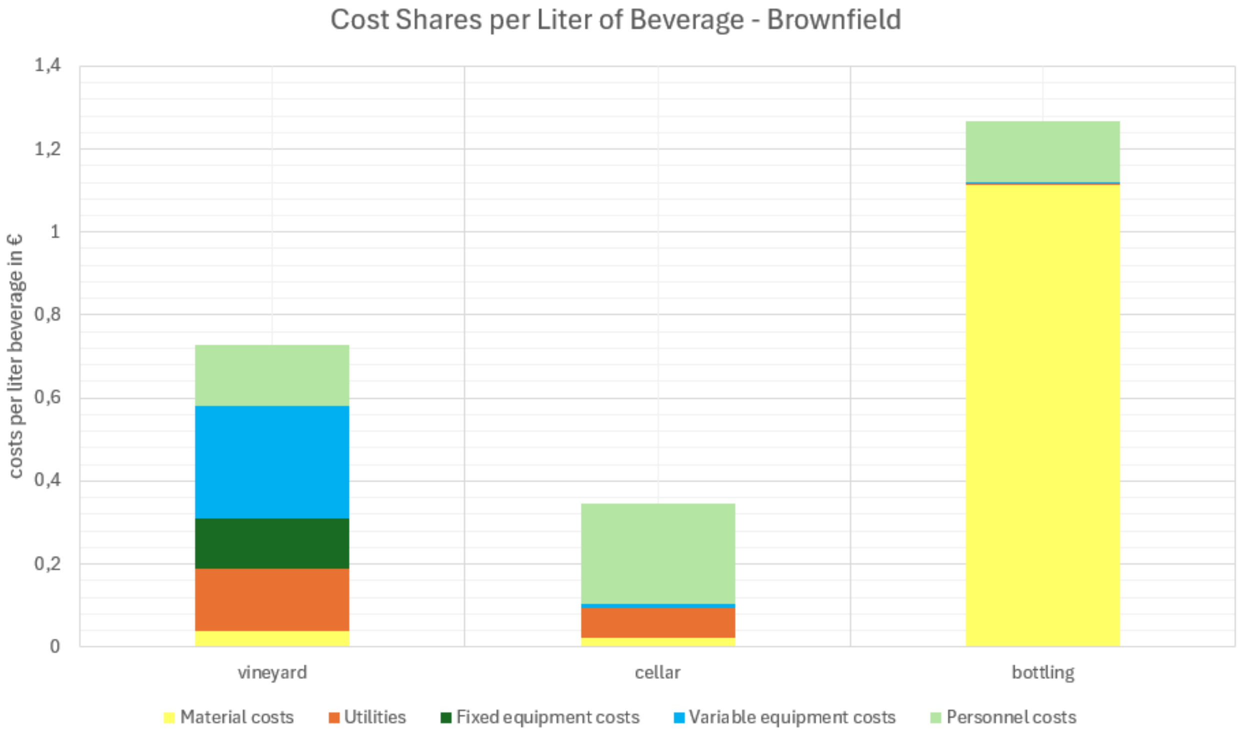

Figure 7: Share of costs per liter of beverage in the brownfield scenario

steps (see Fig. 6) shows that the last step of bottling con-tributes the largest share of costs. This is primarily due to the high material costs (88.2%), with the glass bottle alone representing 54.3% of the total costs in this process step.

In the vineyard process step, the focus is on variable machinery costs (25%) as well as depreciation (32.4%). This structure reflects the high machinery intensity of the work, as described in the relevant literature (Zhang & Rosentrater, 2019; Marone et al., 2017). In contrast, the cellar operations are primarily characterized by personnel costs (68.6%), which is attributable to the high worker intensity of this activity.

To assess profitability, a static economic analysis is conducted. The selling price is set at €10 per liter, based on market-standard wine prices (Weinkenner, 2018). Using a yield of 688.62 L/ha, potential revenue and key performance indicators (contribution margin, EBITDA, EBIT, ROI, payback period) are determined. In the Brownfield scenario, due to the absence of depreciation, both ROI and payback period are not applicable (cf. Table 1).

In summary, the analysis shows that both scenarios, depending on the scale of the facility, offer an

Table 1: Comparison of TEA results for the Greenfield and Brownfield scenarios

Indicator	*Greenfield Scenario*	*Brownfield Scenario*
Margin	371,56%	427,39%
Revenue	6886,20 €/ha	6886,20 €/ha
Contribution Margin	5358,03 €/ha	5358,03 €/ha
EBITDA	5274,91 €/ha	5274,97 €/ha
EBIT	5032,91 €/ha	/
ROI	9,4%	/
Payback Period	10,64 Jahre	/

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economically positive outlook. A profit of €5,032.91 (Greenfield) or €5,274.97 (Brownfield) can be achieved per hectare. The project can thus be considered a profitable supplementary option to traditional wine sales.

Summary

This project investigates the use of PiWi vine leaves as a basis for a fermented, non-alcoholic beverage and demonstrates that this production option is advantageous both environmentally and economically. The environmental assessment, conducted through LCA, identifies the carbon footprint (CF), acidification potential (AP), eutrophication potential (EP), and terrestrial ecotoxicity potential (TETP) as the central impact categories, which are particularly relevant in viticulture due to the use of diesel, fertilizers, and pesticides.

The results show that all five investigated production scenarios of the PiWi beverage score below the reference beverages (fermented limonade, tea-based drink, non-alcoholic wine) in the environmental categories of climate change, acidification, and eutrophication. Notably, the effect of organic PiWi vines in the organic cultivation scenario reduces terrestrial ecotoxicity by approximately 86%. The largest environmental impacts arise from bottling, particularly glass production, and from vineyard operations due to diesel and pesticide use. Scenarios using PET bottles and renewable energy sources demonstrate further potential savings.

The techno-economic analysis shows that production costs are competitive. In the Greenfield scenario, variable costs account for the largest share, with bottling representing the highest individual cost factor. In the Brownfield scenario, the cost structure shifts toward variable costs, as depreciation is eliminated. At a selling price of €10 per liter, the profit per hectare is substantial (Greenfield: €5,032.91; Brownfield: €5,274.97), qualifying the project as an economically attractive complement to traditional wine sales.

Overall, the research project offers a new beverage concept that combines ecological benefits with economic profitability. At the same time, it demonstrates how principles of circular economy and bioeconomy can be implemented in the beverage industry by utilizing by-products from leaf production and reducing pesticide use. The study therefore provides concrete recommendations for a resource-efficient, environmentally friendly, and marketable production of non-alcoholic fermented beverages.

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Appendix

Table 2: Inventory data of the LCA to produce one liter of beverage based on scenario 1

Input	Unit	Quantity	Score	Output	Unit	Quantity	Source
Vineyard							
Fertilizer	Kg/L	0,0309		Vine leaves	kg	0,3	
Diesel	L/L	0,09	(Wetterstein et al., 2016)	Grapes	kg	8,51	(Wetterstein et al., 2016)
Pesticides	g/L	15,62	(Wetterstein et al., 2016)	Pesticide emissions	g	15,62	(Wetterstein et al., 2016)
Water	L/L	2,505	(Wetterstein et al., 2016)	Nitrate (fertilizer emission)	g	41,09	(De Klein et al., 2006)
electricity	kWh/L	0,0042		Nitrous oxide (fertilizer emission)	g	0,8	(De Klein et al., 2006)
				Ammonia	g	5,56	(De Klein et al., 2006)
Cellar							
Vine leave	Kg/L	0,3		Beverage	L	1	
Electricity	kWh/L	0,233		Solid waste	g	2,4	
Water	L/L	1,83					
Cellulose	g/L	1,2					
Kieselguhr	g/L	1,2					
Sugar	g/L	19,5					
Leaves	g/L	300					
Filling							
Beverage	L/L	1		Filled beverage	L	1	
Electricity	kWh/L	0,002	(Plinke et al., 2000)	Wastewater	L/L	0,19	(Plinke et al., 2000)
Aluminum closure	g/L	1,7	(Dinkel et al., 2014)				
Compressed air	NM3/L	0,0007	(Plinke et al., 2000)				
Steam	kJ/L	1	(Plinke et al., 2000)				
Water	L/L	0,19	(Plinke et al., 2000)				
Lubricant	g/L	0,21	(Plinke et al., 2000)				
Glass bottle	g/L	610	(Dinkel et al., 2014)				
Label	g/L	1,8	(Dinkel et al., 2014)				

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Table 3: Inventory data of the TEA to produce one liter of beverage based on scenario 1 (Greenfield)

			Process Step: Vineyard			
Input	*Quantity per 1000 L*	*Cost per 1000 L (€)*			*Cost per Liter (€)*	*Source*
Pesticides	1,96 kg	40 €			0,0400 €	(Schweiger Handel GmbH, 2023)
Fertilizer	3,25 kg	2 €			0,0020 €	(Rheinland-Pfalz, 2025)
Tap water	260 L	0,48 €			0,0005 €	Statisches Bundesamt (o.D.)
Electricity	0,4 kWh	0,10 €			0,0001 €	(Statista, 2025)
Diesel	90 L	150 €			0,1500 €	(Statista, 2025b)
Equipment	*Investment*	*Fixed Costs per 1000 L*	*Variable Costs per 1000 L*	*Depreciation per 1000 L*	*Total Cost per Liter (€)*	*Source*
Narrow-gauge tractor	4.880,01 €	0,03 €	0,83 €	0,07 €	0,0009 €	(Becker et al., 2017)
Pick-up	4.379,50 €	21,64 €	270,32 €	43,09 €	0,3351 €	(Becker et al., 2017)
Box spreader	287,80 €	0,00 €	0,00 €	0,00 €	0,0000 €	(Becker et al., 2017)
Spray boom	425,44 €	0,00 €	0,17 €	0,00 €	0,0002 €	(Becker et al., 2017)
Leaf removal machine	1.438,98 €	0,21 €	0,39 €	0,22 €	0,0008 €	(Becker et al., 2017)
Electric pruning shear	218,97 €	0,00 €	0,18 €	0,00 €	0,0002 €	(Becker et al., 2017)
Understock mulcher	1.188,72 €	0,02 €	0,48 €	0,01 €	0,0005 €	(Becker et al., 2017)
Machine hall	9.239 €	97,25 €	0,00 €	303,60 €	0,4009 €	(Becker et al., 2017)
Work Step	*Quantity per 1000 L*	*Cost per 1000 L (€)*			*Cost per Liter (€)*	*Source*
Pruning	170 h	92 €			0,0920 €	(Becker et al., 2017)
Mulching	2,31 h	1,20 €			0,0012 €	(Becker et al., 2017)
Fertilizing	2,32 h	1,10 €			0,0011 €	(Becker et al., 2017)
Plant protection	43,11 h	22,80 €			0,0228 €	(Becker et al., 2017)
Leaf harvest	6,17 h	31,10 €			0,0311 €	(Becker et al., 2017)
Total Cost for Vineyard				Costs per 1000 L	Costs per L	
				1.079 €	1,0793 €	

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Table 3 (continued)

Process Step: Cellar						
Input	*Quantity per 1000 L*	*Cost per 1000 L (€)*			*Cost per Liter (€)*	*Source*
Sugar	19,5 kg	17 €			0,0166 €	(Bundesanstalt für Landwirtschaft und Ernährung, 2024)
Cellulose filter	1,2 kg	0 €			0,0003 €	(Seitz® T Series Depth Filter Sheets, T 2600 400x400 in cartons – Products, o.D.)
Kieselguhr	1,2 kg	4,79 €			0,0048 €	(Pflanzenkohle24, n.d.)
Electricity	230 kWh	68,96 €			0,0690 €	(Statista, 2025)
Tap water	1830 L	3 €			0,0033 €	(Statisches Bundesamt, o.D.)
Equipment	*Investment*	*Fixed Costs per 1000 L*	*Variable Costs per 1000 L*	*Depreciation per 1000 L*	*Cost per Liter (€)*	*Source*
Destemming machine	1.698,23 €	0,21 €	0,00 €	0,71 €	0,0009 €	(Becker et al., 2017)
Pneumatic press 5000 L	7.507,71 €	0,07 €	0,00 €	0,22 €	0,0003 €	(Becker et al., 2017)
Forklift	3.878,98 €	0,15 €	9,00 €	0,62 €	0,0098 €	(Becker et al., 2017)
Grape bin 600 L, two units	57,56 €	0,02 €	0,80 €	0,04 €	0,0009 €	(Becker et al., 2017)
Pasteurizer	4.629,75 €	0,11 €	0,33 €	0,24 €	0,0007 €	(Becker et al., 2017)
Fermenter 675 L, two units	212,72 €	0,57 €	0,00 €	0,93 €	0,0015 €	(Becker et al., 2017)
Crossflow filtration system	3.816,00 €	0,03 €	0,00 €	0,14 €	0,0002 €	(Becker et al., 2017)
Cartridge filter	989,00 €	0,01 €	0,00 €	0,04 €	0,0001 €	(Becker et al., 2017)
Universal pump	1.001,03 €	0,00 €	0,00 €	0,01 €	0,0000 €	(Becker et al., 2017)
Diatoma-ceous earth dosing device	763 €	0,00 €	0,04 €	0,01 €	0,0001 €	(Becker et al., 2017)

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Table 3 (continued)

Work Step	*Duration per 1000 L*	*Labor Costs per 1000 L*		*Labor Cost per Liter (€)*	*Source*
Chopping	2,33 h	40 €		0,0398 €	(Becker et al., 2017)
Loading mash into press	0,7 h	11,74 €		0,0117 €	(Becker et al., 2017)
Pressing	0,48 h	8,02 €		0,0080 €	(Becker et al., 2017)
Operating forklift	6,67 h	111,83 €		0,1118 €	(Becker et al., 2017)
Filtering	3,13 h	52,50 €		0,0525 €	(Becker et al., 2017)
General cellar work	0,9 h	15,10 €		0,0151 €	(Becker et al., 2017)
			Costs per 1000 L	Costs per L	
			347 €	0,3474 €	
			Process Step: Filling		
Input	*Quantity per 1000 L*	*Cost per 1000 L (€)*		*Cost per Liter (€)*	*Source*
Glass bottle 1 L	1000 bottles	690 €		0,6900 €	(Mura et al., 2023c)
Aluminium closure	1000 closures	120 €		0,1200 €	(Südglas EG | Aluverschluss MCA 28 Weiss für Wein mit Gewinde, o. D.-b)
Other bottle costs		280 €		0,2800 €	(Mura et al., 2023c)
Label	1000 Labels	30 €		0,0300 €	(Mura et al., 2023c)
Electricity	2,44 kWh	1 €		0,0007 €	(Statista, 2025b)
Compressed air 6 bar	0,7 Nm3	0 €		0,0000 €	(Redaktion, 2025b)
Steam	1000 kJ	0,02 €		0,0000 €	(May 2025)
Tap water	190 L	0,34 €		0,0003 €	(Statista, 2025)
Wastewater treatment	190 L	0 €		0,0005 €	Statistisches Bundesamt (o.D.)

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Table 3 (continued)

Equipment	*Investment*	*Fixed Costs per 1000 L*	*Variable Costs per 1000 L*	*Depreciation per 1000 L*	*Total Cost per Liter (€)*	*Source*
Inline fille	1.001,03 €	0,05 €	0,31 €	0,27 €	0,0006 €	(Becker et al., 2017)
Dipping bath sterilizer	4.955,00 €	0,18 €	1,65 €	0,88 €	0,0027 €	(Becker et al., 2017)
cap rolling machine	231,00 €	0,02 €	0,43 €	0,10 €	0,0006 €	(Becker et al., 2017)
Labelling machine	738,00 €	0,04 €	0,70 €	0,20 €	0,0009 €	(Becker et al., 2017)
Work Step	*Duration per 1000 L*	*Worker Costs per 1000 L*			*Worker Cost per Liter (€)*	*Source*
Automatic bottle sterilization	0,7 h	12 €			0,0117 €	(Becker et al., 2017)
Fully automatic small sterilization, filling, and corking system	3 h	50,31 €			0,0503 €	(Becker et al., 2017)
labelling machine, selfadhesive technology	5 h	83,85 €			0,0839 €	(Becker et al., 2017)
Total for bottling process step				Costs per 1000 L	Costs per L	
				1.272 €	1,2723 €	
Total across all process steps		*2,6990 €*				

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