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Practioner‘s Section

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Leveraging Generative AI for Rapid Competitive Landscape Analysis: A Feasibility Study in the Chemical Industry

Competitive analysis is a crucial yet challenging task for chemical companies as it requires synthesizing fragmented financial and market information to assess strategic positioning. Conventional methods are often time-consuming and labor-intensive limiting their scalability, efficiency and adaptability. This study explores the potential of generative AI to overcome these challenges by automating the extraction and interpretation of corporate financial reports and mapping product portfolios to end-user markets based on the Global Industry Classification Standard. By linking these markets to historical growth rates, the presented methodology maps competitive positions and reveals strategic opportunities as well as market risks for selected chemical companies. The AI-powered approach significantly accelerates competitive analysis while ensuring accuracy and reliability. The study concludes with an outlook on how generative AI can further enhance strategic decision-making in the chemical industry and beyond.

Introduction

The chemical industry is characterized by high complexity due to its diverse product portfolios, regulatory constraints, and entangled supply chains (Hiemer and Suntrop, 2017). In the past few years, the chemical industry has been undergoing significant transformation, driven by increasing competition, technological advancements, and regulatory pressures. As traditional business models become less effective in navigating these challenges, companies must adopt new analytical frameworks to sustain competitive advantages (Utikal and Leker, 2018). Historically, strategic analysis has relied on structured methodologies including, for example, expert interviews to derive SWOT (strengths, weaknesses, opportunities, and threats) analysis (Paul, 2010). However, interviews with industry professionals pose the risk of bias from subjective expert opinions and may also lack statistical validation due to limited sample sizes (Dorussen et al., 2005). This and other conventional approaches to competitive analyses in the chemical industry and beyond can be time-consuming and require extensive in-depth industry knowledge (Pleatsikas and Teece, 2001).

Generative AI (GenAI) has become an essential technology enabling automated industry comparisons and financial forecasting due to its capacity to rapidly analyze vast amounts of data (Kumar et al., 2025). While its huge

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potential is recognized by most companies, the practical feasibility of applying GenAI to use cases in the chemical industry remains an open question (Konrad, 2024). This study demonstrates and evaluates the power of leveraging OpenAI's ChatGPT to enhance competitive and strategic analysis in the chemical sector.

In more detail, the authors developed a GenAI-supported approach to evaluate the strategic positioning of ten European chemical companies. Profitability and performance trends were calculated using financial metrics extracted from corporate financial statements by GenAI. Additionally, the algorithm mapped company activities to their corresponding end-user markets, which were then aligned with historical growth rates revealing strategic opportunities. The presented approach demonstrates the potential of using GenAI to efficiently generate competitive landscapes. With the framework at hand, the process can easily be re-applied, allowing for seamless re-evaluation and thus ensuring an up-to-date understanding of the competitive environment.

Future work could further enrich the presented results by incorporating additional information such as press releases on investments, acquisitions, and divestitures providing further insights into companies' strategic direction. Additionally, integrating frequently updated market reports and price forecasts could enable even more dynamic and forward-looking analyses. Finally, the framework could be applied to other asset-heavy industries, making it a scalable approach to future competition analysis.

Literature Review: GenAI for Competition Landscape Analysis

Recent advancements in GenAI enable new ways to conduct structured competition analyses within an industry including the interpretation of financial reports. Generally, there are multiple approaches to screen and interpret reports with GenAI. First, as used in this study, relevant documents can be directly uploaded to ChatGPT and subsequently analyzed. This direct approach is easily implemented while maintaining a robust performance.

Beyond this direct usage of documents, a study by Amazon Web Services demonstrated the benefits of fine-tuning LLMs for summarization and answering questions concerning complex financial documents (Amazon Web Services, 2024). Furthermore, a comparative analysis of retrieval-augmented generation (RAG) by Zou et al. identified the GPT-4 LLM as a leading model for data analysis of environmental, social, and governance reports (Zou et al., 2024). Compared to the approach within this work, LLM fine-tuning and RAG implementation might allow for even more granular results and answers.

Integrating additional sources beyond financial reports provides further opportunities for in-depth industry studies. A GenAI analysis of corporate news, reports and policies was shown to be valuable for stock analysis and investment recommendations (Teo et al., 2024). Similarly, Beckmann et al. found that unusual financial communication extracted with ChatGPT from earnings call transcripts correlates with a negative stock market reaction and can thus be used in stock and company analysis (Beckmann et al., 2024).

In all cases, communication with the GenAI model requires proficient prompts to enable optimal results. Therefore, establishing and fine-tuning prompts – called prompt engineering – has become an essential part of using GenAI. A recent work by Krause explored the capabilities and limitations of different LLMs in financial and company analysis, emphasizing the importance of well-structured prompts to maximize accuracy and relevance (Krause, 2023). The study highlights essential practices, such as iterative prompt refinement, adding domain-specific context, avoiding ambiguity, and cross-verifying AI-generated insights with conventional analytical methods. Additionally, the risks of excessive reliance on AI-generated outputs without human validation, such as the possibility of hallucinated information and challenges in factual validation of the GenAI output, are discussed. Furthermore, Sikha et al. highlighted structured prompting as a key technique to enhance AI interpretability and reliability, demonstrating how adaptive prompt engineering strategies refine AI responses through iterative optimization (Sikha et al., 2023).

Further improvements can be achieved by utilizing open questions and starting conversations with the algorithm. An example of advanced AI interactions is explored by Chukhlomin who introduces "Socratic prompting" as a technique to refine AI-generated responses. By structuring prompts within the question-driven approach, this method helps mitigate biases and improve the depth of AI-generated insights (Chukhlomin, 2024).

Besides providing output in natural language, GenAI can boost the process efficiency of text-processing tasks such as advanced categorization and pattern recognition. As an example, Rizinski et al. showcased the potential of natural language processing in automating industry classification for datasets, since established standards like Global Industry Classification Standard (GICS) traditionally rely on manual

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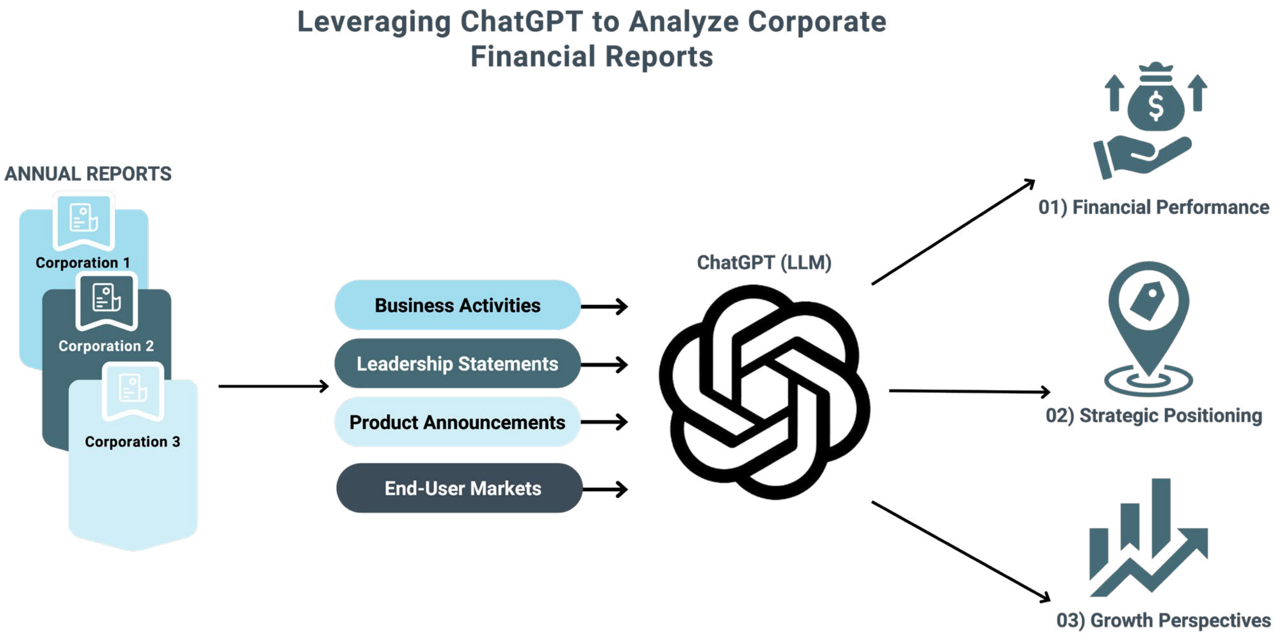
industry assignment by experts (Rizinski et al., 2024). In addition, the paper by Krause also discusses the advantages of AI in accelerating data processing and uncover patterns in vast financial datasets (Krause, 2023).

Overall, GenAI has the potential to minimize the need for manual data gathering, significantly enhancing process efficiency and allowing for rapid analysis of extensive datasets. The practical use case, described in the following sections of this paper, demonstrates these capabilities for competition landscape analysis while providing detailed instructions and showcasing exemplary results.

Methodology

This study deploys a structured analysis utilizing the large language model (LLM) of OpenAI's ChatGPT model 4o to interpret the financial reports from 2021 to 2023 of 10 selected European players in the chemical industry. Namely, these companies are Air Liquide, BASF, Bayer, Covestro, INEOS, Linde, Solvay, Syngenta, Umicore, and Yara. A schematic work and data flow is depicted in Figure 1. The methodology begins with automated data extraction and processing with ChatGPT where financial data is gathered from published annual reports.

Figure 1: Schematic overview of the automated analysis of corporate financial reports with ChatGPT.



For all steps, a dedicated series of prompts was developed. Results were improved by applying several prompt engineering techniques. This includes breaking the tasks of data extraction and interpretation into smaller work packages, automated verification of the extracted data, and giving virtual bonuses to ChatGPT for detailed and thorough extraction of data. Furthermore, the prompt was enriched with exemplary expected results providing validated examples and thus guidance to the LLM. To ease the subsequent analysis and visualization, the prompt also provided how to output the extracted information, i.e., tabular formatting and naming of columns.

For a comparative financial assessment of the companies, revenue and EBITDA figures were extracted from the reports for the fiscal years 2021, 2022 and 2023. Subsequently, the end-user markets, in which the sold products, chemicals and services are ultimately used, were identified. The LLM leverages natural language processing to scan, interpret, and match products with their relevant markets. For instance, in the classification process, the product „Chemicals for surface treatments and coatings for electronics" is automatically identified as being linked to the „Electronic Equipment & Instruments" end-user market. In addition, ChatGPT is asked to explain each mapping of product to end-user market enabling a fast way to validate the extracted data with additional expert knowledge.

The extracted end-user markets were then linked to an industry category of the Global Industry Classification Standard (GICS) system (S&P Dow Jones Indices and MSCI Inc., 2023). The standardized classification ensures consistency in the analysis across different players and allows for direct comparison between these companies

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concerning their strategic positioning in the end-user markets.

Furthermore, every GICS industry was matched to a published compound annual growth rate (CAGR) from 2019 to 2023 (Damodaran, 2024). Finally, all industry growth rates were categorized from low (<5%), medium (5% to 10%) to high (>10%), to provide a semi-quantitative and comparative assessment that enhances understanding of potential market opportunities and growth trajectories for the investigated companies.

Since the GICS industry names differ from the sector names of the published revenue growth rates, we matched the GICS industries with ChatGPT to the revenue growth sectors. The GICS classification comes with a detailed description for every industry. The industry descriptions for the revenue growth sectors were generated with ChatGPT by using the list of companies for each respective sector. The revenue growth sector descriptions were then matched with ChatGPT to the GICS industry descriptions.

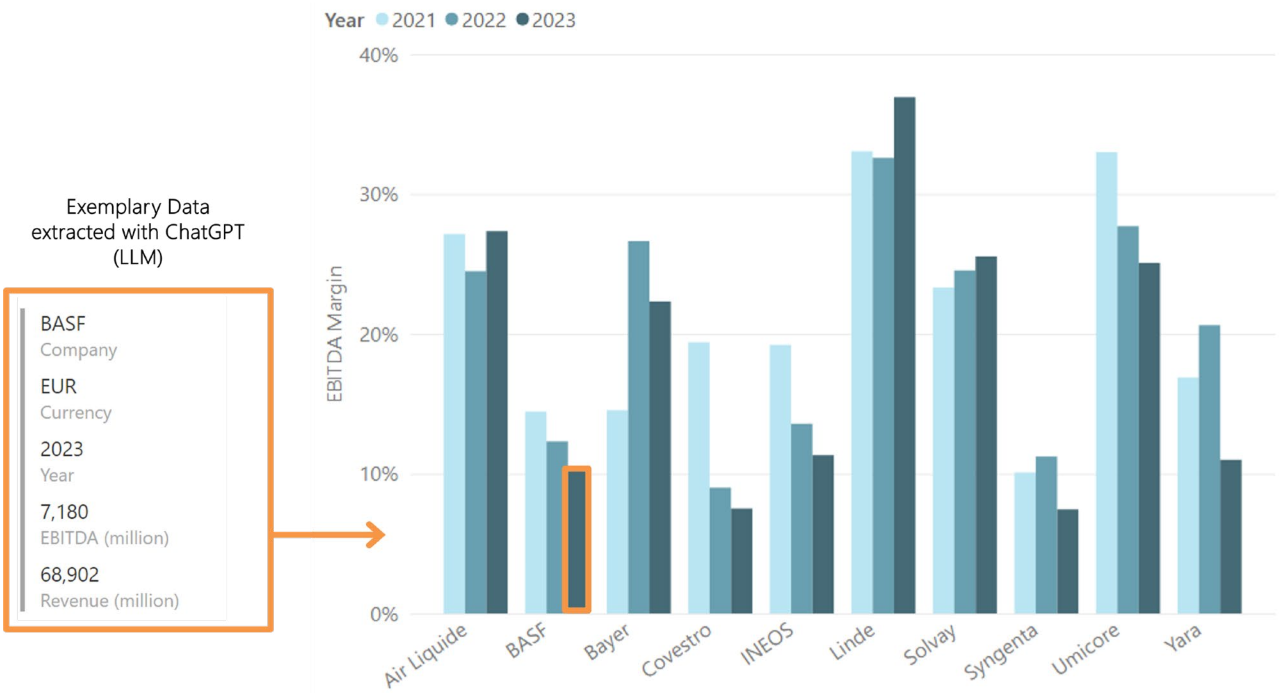
Results

As described in the methodology section, we chose ten chemical companies to demonstrate the potential of GenAI in competitive landscape analysis. Applying the above-described steps using ChatGPT yielded several key insights related to their financial performance, strategic positioning, and market opportunities. By processing publicly available financial reports and annual business statements, the tool successfully extracted financial information and identified end-user markets for each company's products. These comparative analyses provide an initial overview of the individual companies' strategic positioning and the industry's dynamics. The insights derived from this comprehensive analysis are synthesized into a comparative framework that highlights the strategic positioning of the selected chemical companies. This framework not only identifies market opportunities and shortcomings but also recommends strategic opportunities that companies may consider capitalizing in future.

Financial Performance

The GenAI-based approach effectively retrieved and processed the financial data of the selected chemical companies, demonstrating the model's ability to reliably and accurately handle complex financial statements and annual reports. A key metric is the EBITDA margin, which provides insight into each company's operational profitability before interest, taxes, depreciation, and amortization. Figure 2 depicts the results from the semi-automated report screening. This initial financial analysis sets a foundation for understanding both current performance and trends over

Figure 2: EBITDA margin comparison for ten chemical companies from 2021 to 2023 (light to dark blue) as extracted with GenAI from corporate financial reports. An example of raw data gathered by ChatGPT is shown in the orange box for BASF in 2023. The derived EBITDA margins (EBITDA divided by revenue) for all companies are plotted on the right.



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the past three years.

As an example, in 2023 the data displays notable differences in the absolute EBITDA margins across the companies. Linde stood out with the highest margin at 37%, followed by Air Liquide 27%, and Solvay at 26%. These companies exemplify successful execution in niche markets and rank in leading market positions with specialized, high-value products. Among others, products such as industrial gases, advanced materials, and catalysts benefit from stable demand and premium prices. On the other hand, companies like BASF, Covestro and Syngenta reported lower EBITDA margins of 10%, 8% and 7%, respectively. While their diverse product portfolio provides resilience, larger shares of commoditized business areas in the portfolio limit overall profitability. In particular, competition from Asian producers and rising energy and raw material costs create more challenging business conditions while impacting margins for the observed period.

Examining the changes in profitability between 2021 and 2023 reveals varying trajectories among the companies. Linde, Air Liquide, and Solvay maintained relatively stable and high profitability throughout the period. Considering the geopolitical changes and disruptions throughout these years, the companies show high resilience and low volatility against economic fluctuations. In contrast, several companies such as BASF, Covestro, INEOS, and Umicore recorded notable and gradual declines in their profitability. This can be interpreted as a sign of a more cyclical product portfolio and overall higher price sensitivity.

While comparing EBITDA margins across companies and years is a basic analysis, the results establish a baseline understanding of financial health and profitability trends within the sector. To gain a more comprehensive view of growth trajectories and investment in potential opportunities, additional financial metrics could be integrated into the model. Metrics such as R&D-to-sales ratio, CAPEX trends, cash flow, debt-to-equity ratio, and ROE/ROA would offer valuable insights not only into current performance but also how well-positioned each company is for organic and sustainable growth. However, in this analysis, these metrics were not included due to an overall inconsistent reporting on the mentioned KPIs across the selected companies.

Strategic Positioning

Next, the ChatGPT framework was used to extract and categorize the companies' business activities and product applications in end-user markets. This approach allowed for a detailed mapping of each company's strategic focus across different subsegments, such as specialty chemicals, agricultural chemicals, and consumer products (Figure 3). The matrix highlights each company's relative allocation of identified end-user markets. The color intensity in each cell reflects the strategic focus based on qualitative data from the annual reports such as product announcements, leadership statements, or summaries of business activities. The model's capability to provide explanations for individual data points in the matrix was highlighted with two exemplary results (Figure 3, left), also allowing easy validation and deeper understanding of the data. Note, the assignment of products to their corresponding end-user markets is conducted through a fully automated process, significantly reducing the effort that a manual categorization would entail.

The analysis demonstrated the ability of GenAI to accurately distinguish between relevant and irrelevant GICS sectors for the displayed chemical companies. For sectors such as real estate, financials, and communication services, which are less aligned with the core operations of chemical companies, only few examples were found and are thus not shown here. This capability underscores the model's precision in focusing on sectors and end-user markets directly tied to the chemical sector, such as materials, consumer staples, industrials, and energy, ensuring results remain relevant and actionable.

A key insight from the heatmap is the contrast between companies that pursue broad diversification and those that adopt specialized strategies. Diversified companies, such as BASF and INEOS, display dependencies across multiple segments, with e.g., BASF balancing its portfolio towards materials, consumer staples, and consumer discretionary sectors. INEOS exhibits a similar approach, balancing its activities with commodity and specialty chemicals towards various end-user markets in construction, household products, and automotive. In contrast, the heatmap shows a more concentrated focus for companies like Syngenta and Bayer.

The analysis can further provide an indication of competition and leadership dynamics within certain subsegments. For example, Agrochemicals is an area where the matrix shows several companies such as Bayer, Syngenta, and Yara with highlighted activities, hinting at direct or distant competition in the market. However, such overlap also suggests opportunities for collaboration, especially in areas where shared interests align, such as improving efficiency, co-development & innovation, or advancing sustainability initiatives. By leveraging these common

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goals, companies could potentially reduce costs, accelerate development cycles, or address broader industry challenges collaboratively. Additionally the analysis also highlights leadership in specific markets with minimal competition between the selected companies. For instance, Linde's and Air Liquide's focus on industrial gases positions them with a limited direct overlap from other companies within the analysis.

The heatmap further highlights differences in dependence on cyclical versus non-cyclical industries. For example, companies with significant ties to construction materials, automotive, and manufacturing may experience more pronounced sensitivity to economic cycles, which can introduce volatility in short- and mid-term performance. In contrast, companies with a focus on agricultural products, consumer staple goods, and pharmaceuticals/healthcare operate in markets for which demand remains relatively stable over time. These markets are driven by factors such as population growth or food security needs. The model's breakdown can therefore indicate how portfolio composition and market activities result in different exposures to cyclical and non-cyclical business in the peer group.

The analysis demonstrates the model's ability to extract and categorize business activities, accurately map strategic priorities, and identify key elements of competitive positioning within the chemical companies at hand.

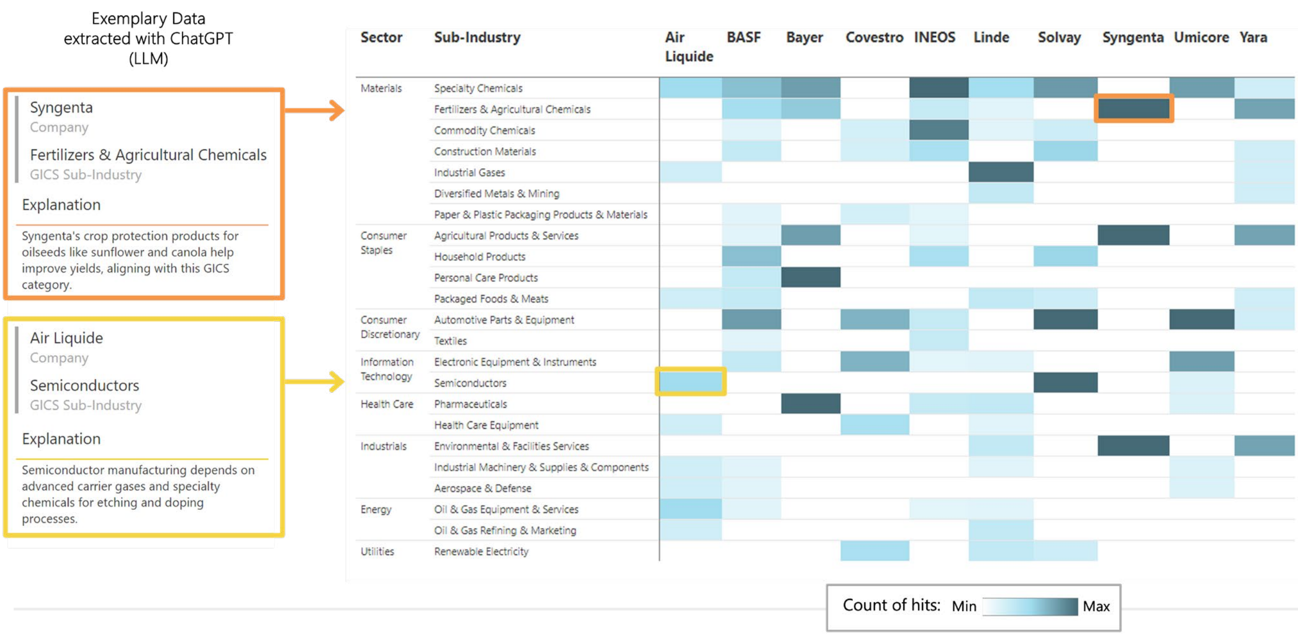
Market Opportunities & Risks

Next, the strategic focus of each company is linked to historical industry growth rates of the identified end-user markets. As described in the methodology section, each company's activities were linked to high-, moderate-, and low-growth sectors based on compound annual revenue growth rates (CAGR) from 2019 to 2023 (Figure 4). From dark to light blue, the data represents high-growth (>10% CAGR), moderate growth (5–10% CAGR), and low-growth segments (<5% CAGR). Identified sub-industries with high growth during past years are, for example, pharmaceuticals, agricultural products, and electronic equipment. While fertilizers, automotive parts, and building materials showed moderate growth, examples of sub-industries with low growth are household products, paper packaging, and agricultural machinery.

Mapping the end-user markets, as identified for each company's products into these three categories provides a detailed perspective on how chemical companies are aligned with growth opportunities across their portfolios (Viguerie et al., 2011). Furthermore, the graph shows the portfolio alignment of each company with growing markets, revealing notable differences in resource allocation and strategic focus. The data shows varying degrees of alignment with market trends, capturing opportunities, and insights into competitive positioning across the industry.

In more detail, the visualization reveals clear differences in strategic positioning across companies. Companies with a significant share of high-growth segments, like

Figure 3: Strategic positioning of key chemical companies across GICS industry sectors and sub-industries, highlighting the concentration of business activities. Darker colors indicate stronger focus areas within specific sub-industries. In the orange and yellow boxes on the left side, two with ChatGPT extracted exemplary data points of identified GICS industry and matching explanation of identified end-user market to GICS industry are given.



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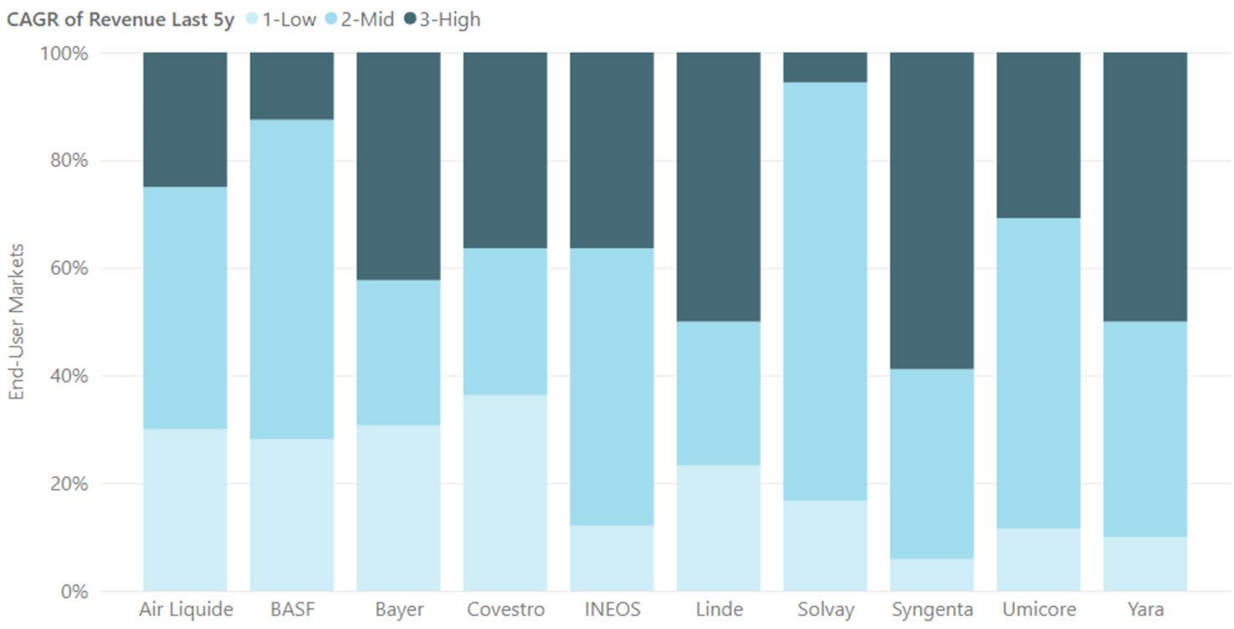
Syngenta and Linde, appear well-positioned to capitalize on expanding demand in fast-growing markets, such as semiconductors, pharma, and agriculture. This alignment may provide potential competitive advantages in capturing growing demands. In contrast, companies with significant activities in moderate- and low-growth segments, like Solvay and BASF, may face challenges in achieving significant growth, as these segments tend to experience greater market stability but lower growth potential. Such portfolio compositions could introduce strategic risks due to missing growth opportunities in the long run.

The analysis further provides insights into portfolio resilience. Companies with a balanced distribution across high-, moderate-, and low-growth segments could mitigate risks associated with volatility in individual categories. Firms blending high-growth opportunities with stable mid-growth markets might buffer against fluctuations while maintaining steady long-term growth. Conversely, companies focused heavily on high-growth markets may face greater exposure to market shifts, while those weighted toward low-growth areas risk stagnation without strategic adjustments.

By comparing this chart (Figure 4) with the heatmap of strategic focus (Figure 3), additional insights emerge. Companies heavily specializing in high-growth segments may also exhibit niche dominance in the heatmap, signaling deliberate alignment with emerging trends. As an example, Syngenta provides products to a few markets that however showed robust growth during past years. Conversely, firms balancing high-, moderate-, and low-growth areas often align with diversified strategies that emphasize risk mitigation. The balanced approach is identified, for example, for INEOS, which additionally enables products in many end-user markets. Identifying mismatches between growth opportunities and strategic focus provides valuable opportunities for companies to adjust their priorities or reallocate resources. Besides the positioning in growing markets, the profitability that can be achieved within an industry plays a crucial role in achieving high margins. While Syngenta and Linde both sell into growing markets (Figure 4), the specific profitability depends on the individual end-user markets. This also hints at differences in these companies in terms of EBITDA margin (Figure 2). Including the dimension of average profitability in each industry could enrich the analysis in future.

Overall, the results highlight the varying degrees of future readiness among chemical companies. Firms with a strong presence in high-growth segments appear better positioned to seize market opportunities, while others may need to adapt their strategies to address market dynamics. By linking growth potential with existing market focus, the tool enables a forward-looking perspective on competitive positioning and portfolio optimization. Next, the precision and reliability of the GenAI-based results are elaborated.

Figure 4: End-user market growth across key chemical companies. Three categories are defined with revenue CAGR in the industries during the last 5 years: Green represents high-growth segments (>10% CAGR), grey indicates moderate growth (5-10% CAGR), and red signifies low growth (<5% CAGR).



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Evaluating GenAI Output

To ensure the accuracy and reliability of the AI-generated insights, a thorough validation process was deployed. Firstly, by cross-checking selected financial metrics and the end-user market interpretations against the respective corporate annual reports, the prompts used for extraction and analysis were improved. This iterative process of improving the prompts and subsequently reevaluating the AI-generated insights ensures reliable data extraction. The output was then tested for consistency across multiple cycles. By running the tool on the same dataset multiple times, we ensured that it consistently produced highly similar insights each time.

The GenAI-extracted EBITDA and revenue figures were also compared against publicly available data. Thereby, significant outliers were identified in less than 5% of the extracted financial metrics. For this work, the outliers were manually corrected to ensure an accurate analysis of the financial performance.

The accuracy of mapping chemical products to end-user markets was further evaluated for two exemplary companies. Therefore, the end-user markets were additionally extracted using only corporate websites and mapped subsequently to the GICS industries. This was done by using the same prompts as within the ChatGPT analysis of the annual reports. Comparing both methods reveals a high overlap of the results: 87% of the GICS industries extracted from the annual reports were also found in the list of GICS industries from corporate websites. The remaining GICS industries from the annual reports were most likely not identified on the corporate websites, since not all business areas and projects are reported on the same level of detail in the annual reports and corporate websites. Furthermore, business focus might have shifted and thus business areas are not mentioned anymore on the corporate websites that were analyzed at the end of 2024, compared to the 2023 annual reports.

Besides the validation techniques used in this work, various further approaches can be applied. A more sophisticated way was used by Bouteraa et al. who conducted semi-structured expert interviews to gain insights on the banker's perspectives and willingness to use ChatGPT (Bouteraa et al., 2024). These expert interviews can provide helpful insights but can be time-consuming to set up and conduct. Furthermore, comparing AI-generated insights to published key performance indicators offers a quantitative means of validation (Moreno and Caminero, 2024). However, variations in calculation methods or underlying assumptions can introduce discrepancies between metrics. In a recent study from Apple, Mirzadeh et al. found no evidence of formal reasoning in LLMs. Moreover, minor changes to inputs, such as altering variable names or introducing irrelevant information, significantly affected the model accuracy (Mirzadeh et al., 2024).

These studies show that combining expert validation, quantitative comparison to KPIs from other sources, and stress testing of prompts as well as the generated output are essential in establishing a robust framework with GenAI-generated outputs that are trustworthy.

Limitations

While the tool demonstrated significant capabilities in generating detailed insights from financial and strategic data, several limitations were identified. As a language processing model, the tool relies exclusively on publicly available corporate reports and disclosures. These documents are prepared to meet regulatory requirements and communicate strategic priorities, which may not always include the full scope of a company's operational details. Consequently, the analysis is contingent on the level of transparency and granularity provided in these disclosures.

An additional limitation arises from the inability to quantify the revenue or profit contributions of specific segments due to the lack of detailed financial breakdowns in many public reports. While the tool can identify a company's presence in specific segments and assign them to end-user markets, it cannot assess the relative financial significance of these segments within the company's overall portfolio.

The tool's reliance on historical data further means that recent strategic adjustments or emerging trends are only captured if explicitly documented. While the mapping of end-user markets to GICS industries provides a standardized framework for comparison, inconsistencies may arise when corporate product terminology or definitions deviate from those established by the GICS system. These considerations emphasize that the analysis offers a structured and efficient approach to understanding competitive positioning and market alignment. It is most effectively applied as an initial framework, which can be supplemented with expert interpretation and additional validation to achieve a more comprehensive strategic assessment.

In terms of usability, the approach proved accessible for non-technical users, offering a practical solution for business analysts and decision-makers who need to quickly generate comparative insights. The automated nature of the tool

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reduces the need for manual data collection and synthesis, allowing companies to focus on strategic decision-making rather than time-consuming data processing. The tool significantly reduced the time required for comprehensive competitive analysis, which traditionally would have taken several weeks to perform manually.

Conclusion

This study demonstrates the potential of OpenAI's ChatGPT to automate and streamline competitive analysis in the chemical industry. The methodology presented serves as a framework for conducting detailed, data-driven assessments of industry players. By utilizing the prompts of this work, the approach allows for quick adjustments to new industries, alternative metrics, or evolving market conditions—overcoming the barrier of starting from scratch. The analysis of financial data, end-user market positioning, and industry growth rates enables a comprehensive, multi-dimensional comparison of companies. This not only provides valuable insights into each company's financial health and strategic positioning but also helps identify potential market opportunities and risks based on sector-specific growth trends. By correlating business segments with market growth rates, companies are assessed in their competitive position in growing markets.

In addition to its analytical depth, the reusability of the framework is one of its greatest strengths. Once the initial prompt system is set up, the model can be easily updated with new data and applied across different sectors, making it a scalable solution for competitive analysis in various industries. This continuous adaptability ensures that companies can maintain an up-to-date understanding of their competitive landscape without the need for costly and time-consuming manual analysis.

While the tool enhances the efficiency and speed of generating competitive landscapes, it is important to note that AI-driven analysis is dependent on the quality and availability of public data. In industries like chemicals, where strategic nuances and long-term vision are often complex, some qualitative aspects still require human interpretation and expertise. However, as a tool for rapid synthesis of quantitative data and strategic positioning, GenAI offers significant potential for augmenting human decision-making.

In conclusion, this feasibility study underscores the potential of GenAI to enhance strategic analysis in the chemical industry. The presented methodology offers an adaptable and efficient approach for competitive analysis. Future work could further enhance the results by exploring its predictive capabilities and expanding its application across other asset-heavy industries facing similar analytical challenges. By integrating AI-driven insights with established industry standards, companies can gain a deeper understanding of market dynamics, proactively identify risks, and strategically adapt to evolving challenges.

Declaration

During the preparation of this work the authors used GPT-4o in order to improve readability and refine language. After using AI-assisted revisions, the authors thoroughly reviewed and edited the content as needed.

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