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## Article

# Artificial intelligence and smart manufacturing: An analysis of strategic and performance narratives

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**ARTIFICIAL INTELLIGENCE AND SMART MANUFACTURING:  
AN ANALYSIS OF STRATEGIC AND PERFORMANCE NARRATIVES**

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**Abstract**

This paper examines how artificial intelligence and smart manufacturing concepts are reflected in the business strategy and performance narratives of major industrial corporations. A qualitative analysis of annual reports from the 20 largest global industrial companies listed on US stock exchanges was conducted using QDA Miner software. The analysis focused on uncovering connections between smart manufacturing, strategy, and performance themes based on code frequencies, co-occurrences, and proximity, being the first study in the literature with this objective. Through this methodical analysis of the association between 'smart' technologies and the strategic elements of companies in the industrial sector, present in the investor interface represented by annual reports, the article contributes to a better understanding of how technological development has shaped this economic sector. Key findings reveal that while smart manufacturing codes were less frequent, 'robots and automation', 'cybersecurity', and 'sensors' displayed higher frequencies, reflecting an emphasis on Industry 4.0 integration. Cluster analysis uncovered a prominent linkage between 'cybersecurity' and strategy/performance codes, highlighting its growing influence. Additionally, concepts such as 'artificial intelligence', 'cloud' and 'digitalization' showed robust connections with strategy/performance code. The analysis emphasises the strategic prioritisation of technological innovation to enhance operations and competitive positioning. Overall, the study's investigation of annual reports underscores technology's profound impact in shaping strategic objectives, performance frameworks, and operational approaches within the manufacturing sector. The observed correlations illuminate the critical interdependencies between smart manufacturing, strategy formulation, and the realisation of

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operational excellence. This research contributes valuable qualitative insights into the evolving digital landscape of industrial practices.

**Keywords:** artificial intelligence (AI), smart manufacturing, qualitative analysis, business strategy, corporate performance

**JEL Classification:** L60, L21, O32, M21

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## **Introduction**

Adopting innovation and emerging technologies, such as artificial intelligence (AI), can greatly improve organisational performance by increasing efficiency, creating new income opportunities, and lowering costs. AI-based automation and data analytics improve operational efficiency, while these technologies enable firms to enter new markets and value pools by enabling novel business models and product offers. A manufacturing company, for example, can use AI-based automation in its production line to optimise procedures and decrease errors, resulting in higher productivity and cost savings. Furthermore, by applying data analytics, the organisation can analyse client preferences and industry trends to produce distinctive products that respond to specific market demands, obtaining a competitive advantage and growing revenue potential. The industrial powerhouses in North America, Europe, and Asia started pursuing a significant modernisation of manufacturing through deliberate policies and strategies that foster digitalisation and the integration of cyber-physical systems, or CPS (Li et al., 2017).

A recent report by McKinsey & Company highlights the strategies that allow leading companies to integrate sophisticated technologies into innovative business models aiming at securing future growth (Banholzer et al., 2023). Intelligent manufacturing systems are drafted around the extensive use of AI and are structured around the coordination of the soft and hard production layers, through a network of sensors and control terminals with a service layer containing intelligent support and operation management software powered by AI engines (Li et al., 2017). Multimodal interfaces can leverage smart sensors, artificial intelligence, and intuitive GUIs to offer engineers and workers a mechanism to engage more efficiently with machines and robotic systems on the factory floor (Mocan et al., 2016). For manufacturers, AI technologies can enhance B2C operations, providing customers with uninterrupted digital assistants and virtual shops, as well as B2B activities through supply chain automation and predictive tools that can adapt to disruptions in demand, supply, and workforce (Zhuo et al., 2021). Another foreseen benefit of generative AI is the substitution of human workforce employed in menial or time-consuming tasks, often in knowledge-intensive fields. More than half of the work-related tasks have the potential to be automatised with the help of AI. Estimates show that the mid-point of AI automation of current work activities will be reached between 2030 and 2060 (Chui et al., 2023).

Digital transformation has both a direct and indirect positive effect on competitive advantage and cost efficiency, although this outcome can be felt only after a certain threshold is reached. In essence, companies are expected to undergo significant investments, sometimes to an extent that can be matched only by the largest of them to fully draw the production and managerial benefits of smart technologies (Li et al., 2023). However, the adoption of AI tools is slowed down by several cultural speed-bumpers: risk aversion, technological illiteracy,

and a sequestered mindset, all leading to impaired digital transformation and reduced investments (Banholzer et al., 2023). Therefore, an inquiry into the ethos of large manufacturers is required if we desire for digitalisation to be achieved at its fullest.

The literature covering the development of smart manufacturing is robust and revolves mainly around case studies, conceptual discussions, technologies, and theoretical issues (Kamble et al., 2018). However, a glaring lack of studies aimed at investigating the entrepreneurial and economic aspects of industrial digitalisation is noticeable. This research paper complements the existing thematic literature by examining the coevolution of smart manufacturing, business strategy, and performance in representative companies from the industrial sector. The objective is to ascertain the overall adoption of smart manufacturing and AI by examining the annual reports of the largest 20 companies in the industrial sector listed on the largest stock market in the world, the United States, using qualitative data analysis software (Provalis Research's QDA Miner). The mixed-method content analysis performed and presented in the paper includes frequency, co-occurrence, and proximity analysis of the textual sources. The research question to which the study provides an answer is the following: To what extent and how do companies in the industrial sector integrate AI and smart manufacturing tools into the discourse on firm strategy and performance, as reflected in annual reports?

Four sections make up the rest of this study. The review of the scientific literature section offers insight into the discussions in existing scholarly works related to our topic, while the next section presents the methodological approach. They are followed by a section that outlines the main findings and discusses their implications. The conclusions section serves as a comprehensive wrap-up of the study, providing an overview of the research's contributions and potential avenues for further exploration.

### **1. Review of the scientific literature**

Industry 4.0, among other technologies, most commonly encompasses the Internet of things (IoT), advanced human-machine interfaces, authentication and fraud detection, 3D printing, smart sensors, Big Data, multilevel customer interaction and profiling, augmented and virtual reality, on-demand availability of computers systems resources, cloud computing, simulations, and integrated autonomous systems (Helmold and Terry, 2021). Four of the core design principles of Industry 4.0 are interconnection through technologies such as the Internet of Things, informational transparency between network nodes, technical assistance through cyber-physical systems, and decentralised, autonomous decision-making through the power of machine intelligence (Hermann et al., 2016).

The adoption of innovation and emerging technologies such as artificial intelligence (AI) can have a profound impact on the companies' financial and operational performance (Enholm, 2021). Academic research has explored various performance-enhancing pathways through which AI adoption improves productivity, creates new revenue opportunities, reduces costs, and provides competitive differentiation. For example, Aggarwal et al. (2022) showed that AI-based applications and tools have significantly improved the operational performance of companies in several sectors of the Indian economy, allowing for better management of operating costs, thus leading to higher profits. In the same vein, Quispe et al. (2023) concluded that AI has a considerable impact on business processes, reducing operating costs

by 26%, increasing the quality of products and services by 30%, and simultaneously generating profit margin increases of 20% for Spanish companies.

At the core, AI technologies such as machine learning (ML) and natural language processing (NLP) automate tasks and augment human capabilities, allowing companies to conduct business operations more efficiently. AI streamlines processes from production to customer service with higher consistency, lower errors, and quicker turnarounds compared to manual approaches (Davenport and Ronanki, 2018). Intelligent algorithms also extract insights from vast data that are impossible for humans to analyse. Data-driven AI models facilitate predictive analytics for forecasting demand, predicting equipment failures, optimising supply chains, and informing business strategy (Seyedan and Mafakheri, 2020). The innovative capabilities unlocked by AI also allow companies to create innovative business models, launch AI-enabled products/services, and expand into new markets. Companies commercialising AI can realise novel revenue streams and first-mover advantages. However, truly capitalising on AI innovation requires organisational learning and a solid business strategy that allows companies to expand their knowledge base and dynamically adapt processes to integrate AI (Ahn et al., 2016). Therefore, the performance gains from adopting AI are contingent on how adeptly companies incorporate AI-based platforms into operations and strategy, and these depend on the scope and scale of implementation, availability of quality training data, and ongoing upgrades as algorithms improve (Lee et al., 2022).

The downside of the accelerated digitalisation of the industrial sector manifests itself in a growing cyber risk. Reliance on cloud computing, the Internet of Things, and other network-based technologies enables malign agents to target both informational and technological assets, leading to material and reputational damages and warranting better cybersecurity measures and the insurance of the financial assets (Eling and Schnell, 2016).

Stakeholder theory asserts that, for a company to exist, it needs to uphold several social contracts with different interest groups and garner their support. Management is accountable to these stakeholders, bearing the responsibility of responding to their expectations by disclosing company-related information through candid reports (Deegan, 2006). In the same vein, legitimacy theory recognises the need to account for external factors in decision-making and adapt to changes in their environments (Guthrie et al., 2004).

Corporate reporting and an efficient investor interface are requisite in chartering transparency and relaying information to both regulatory bodies and stakeholders. Annual reports have a pivotal role in acting as a self-issued presentation of a company, attempting to shape the perception shareholders and potential investors have towards it (Iliev et al., 2021). Carrying evidence of corporate strategy and the board's approach to risk exposure, annual reports have the benefit of being unassuming measurements of the company's direction. For the average reader, the narrative presentation of the report is more effortlessly understood than the financial statement section. But it can also be warped with greater ease. As various scholars have pointed out, it would not be uncommon for some reports to be unseemly optimistic toward future business growth (Balata and Breton, 2005). This is often the case in CSR reporting where jargon use and overly positivism can harm the reliability of the message in front of stakeholders (Lock and Seele, 2016).

Through content analysis techniques such as word coding, a snapshot of the company in question can be extracted, and even longitudinal studies can be conducted to examine the changes that occurred over time (Bowman, 1984). Applying content analysis to annual

reports is a common practice used in the study of corporate social and environmental responsibility, as well as in the study of intellectual capital reporting, although this topic seems to suffer from inconsistent data-gathering instruments (Guthrie et al., 2004). However, works that examine companies' annual reports to evidence the reflection of technological developments and innovation in business strategies and outright performance are missing, which offers a significant contribution potential to our study.

Some examples of researchers resorting to qualitative data analysis using software tools for corporate communication content analysis are: Mousa and Elamir (2018) study of Bahraini companies' financial reports for disclosures of forecast and future projects where descriptive statistics and Pearson's correlation coefficient was computed; Ramanauskaitė and Laginauskaitė (2015) content analysis of reports by Baltic Nasdaq listed companies with the aim of identifying statements and insights related to intellectual capital; Penco et al. (2017) analysis of the mission statements published by companies from the cruise industry aimed at collecting information about the management's perspective on the issue of sustainability, CSR and business strategy; a study of philanthropic and civic involvement disclosures in the annual reports and annual sustainability reports of Spanish, French, German and Dutch companies accompanied by word and syntagma frequency analysis with the help of WordStat (de- Miguel- Molina et al., 2015).

Unfortunately, the shortcomings of content analysis are intrinsic to its concept. Despite its powerful auto-coding feature, the risk of QDA Miner generating superfluous codes and overemphasis word recurrence still exists, requiring close monitoring of the results and input materials by the user. The lack of clear benchmarks or guidelines for interpreting the statistical methods employed by QDA Miner or configuring its parameters requires a rigorous understanding of the field in question and inductive processing of source material (Van Haneghan, 2021). The use of paragraphs as a counting unit is preferred to that of words or sentences when trying to derive insight from narrative segments, and measurement of both code and categories is advised (Guthrie et al., 2004). Because the number of coding errors increases alongside the number of categories, the latter should be kept on the lower side. We have weighted the aforementioned factors and deemed QDA Miner to be a serviceable tool for the analysis contained in the following section.

## **2. Research methodology**

Our research portends on the 20 largest global companies in the manufacturing sector listed on stock exchanges in the United States according to their market capitalisation at the end of 2022. We opted for the companies listed in the same country, which also hosts the largest equity markets globally due to the need of standardisation of their annual reports that would provide the basis for our analysis. Data about companies' market capitalisation and their 10-K Annual reports were collected from the Refinitiv platform using the 'Industrials – Industrial Goods' category in the TRBC (The Reference data Business Classification) Sector classification. The 10-k annual reports are comprehensive filings that publicly traded companies must submit to the US Securities and Exchange Commission (SEC) each year. These reports provide an in-depth synopsis of companies' performance that refers to business overview, risk factors, market analysis, audited financial statements, and detailed management discussion. Due to their scope and standardisation, these reports offer transparency into a company's operations and financial health for market regulators, but also

for investors and stakeholders. Although the sample of companies used is not representative of the entire industrial sector, studying the annual reports of the largest companies provides a very good perspective on the developments in the sector, considering that these companies are the most likely to integrate artificial intelligence and smart manufacturing tools.

The sample companies’ market capitalisation at the end of 2022 varied between 29.5 USD billion and 148.36 billion USD, with an average of 65.25 billion USD. Of the 20 companies, eight belong to Electrical Components & Equipment, seven to Aerospace & Defence, three to Heavy Machinery & Vehicles, and one each to Heavy Electrical Equipment and Industrial Machinery & Equipment. Of the 20 companies, 19 are listed on the New York Stock Exchange (NYSE), the flagship stock exchange in the world, and one is listed on NASDAQ, the second market in terms of market capitalisation in the United States and at the global level. Also, 16 companies are headquartered in the United States, three in Ireland, and one in Switzerland. Table no. 1 presents the 20 firms.

**Table no. 1. Sample companies**

Company	TRBC Industry Name	Market capitalisation 2022 (USD billion)
RTX Corp	Aerospace & defense	148.36
Lockheed Martin Corp	Aerospace & defense	127.50
Deere & Co	Heavy machinery & vehicles	127.41
Caterpillar Inc	Heavy machinery & vehicles	124.67
Boeing Co	Aerospace & defense	113.53
Northrop Grumman Corp	Aerospace & defense	83.98
General Dynamics Corp	Aerospace & defense	68.12
Eaton Corporation PLC	Electrical components & equipment	62.42
Emerson Electric Co	Electrical components & equipment	56.81
Johnson Controls International PLC	Electrical components & equipment	43.95
L3Harris Technologies Inc	Aerospace & defense	39.64
Trane Technologies PLC	Electrical components & equipment	38.71
Parker-Hannifin Corp	Industrial machinery & equipment	37.37
TE Connectivity Ltd	Electrical components & equipment	36.42
Carrier Global Corp	Electrical components & equipment	34.50
Paccar Inc	Heavy machinery & vehicles	34.42
TransDigm Group Inc	Aerospace & defense	33.02
Otis Worldwide Corp	Heavy Electrical Equipment	32.62
AMETEK Inc	Electrical components & equipment	32.09
Rockwell Automation Inc	Electrical components & equipment	29.56

*Source: Refinitiv Eikon, 2023*

The texts of the 20 annual reports (each represents a ‘case’) were read thoroughly and then included in a document that was further analysed using Provalis Research QDA Miner 6.01.11, a qualitative data analysis software. This software can process a wide variety of text document formats, including MS Word and PDF and has added features of frequency and statistical analysis. The main advantage of QDA Miner is its versatile coding function, powerful search engine, and included quantitative operations, being favoured in mixed-method research (Lukito and Pruden, 2023). The examination of qualitative data using quantitative-based software has flourished in the recent years, the scopes of these content analyses varying from customer relationship management as evidenced by retail trade

journals (Anderson et al., 2007), recreational attitudes (Stepaniuk, 2017), online product reviews (Islam et al., 2021), or women entrepreneurship (Zaharia and Hassan, 2021) to name only a few areas of research.

In line with our research objective but also based on the content of the annual reports, we identified three major themes: Smart manufacturing, Strategy and Performance. Each of these themes was associated with codes applied to the content of annual reports. There were 19 codes used in the document, presented in Table no. 2. The coding was conducted in paragraphs. After the software identified relevant paragraphs for the words used in coding, the authors verified the resulting content manually to ensure the reliability of the data. There were four coding sessions conducted in teams formed of two authors whose results were cross-checked, and the final coding was decided in a session attended by all authors.

**Table no. 2. Categories, codes and words searched in document**

Categories and codes	Words searched
<i>Smart manufacturing</i>	
Digitalisation	Digitalisation, digital, digitally, digitalised, digital transformation, digital engineering, digital capability/capabilities, digital leadership
Artificial intelligence	Artificial intelligence, AI
Big data and analytics	Big data, analytics
Robots and automation	Robots, robotics, automation, automated
Cloud	Cloud
Internet of Things	Internet of Things, IoT
Sensors	Sensors
Computing	Computing
Cybersecurity	Cybersecurity, cyber
<i>Strategy</i>	
Competitive advantage	Competitive advantage, advantage, position, competition, positioning, market share
Differentiation	Differentiation, differentiator, differentiate, differentiated
Innovation	Innovation, innovative
Product development	Product development
Research and development	Research and development, R&D
<i>Performance</i>	
Growth	Growth, growing
Profitability	Profitability, profitable
Efficiency	Efficiency, efficient
Productivity	Productivity, productive
Agility	Agility, agile

The codes were analysed in terms of frequency (how often were they mentioned in the reports), considered individually and jointly, and similarity. The similarity between codes takes the form of co-occurrence between any two codes. The co-occurrence is the situation when two codes appear together in paragraphs and have been determined using all cases. We have used Sørensen's coefficient (Sørensen, 1948), a version of the better-known Jaccard's coefficient, but more suitable for determining stronger co-occurrences because it gives double weight to codes' co-occurrences in the same paragraph, compared to the equal weight of the Jaccard's coefficient. The formula for the Sørensen's coefficient between two codes is:

$$Sorensen's\ coefficient\ (SC) = \frac{2a}{2a+b+c} \tag{1}$$



In equation (1), *a* designates situations where both codes are present, *b* situations where only the first code is present, and *c* marks situations where only the second code is present. A higher value of the coefficient indicates a greater similarity between codes.

The similarity index was further used to identify clusters of codes across the document. The general objective of cluster analysis relies on revealing groups of entities (codes, in our case) formed naturally, without knowing beforehand how these entities may be included in groups (Hennig et al., 2015). In QDA Miner, hierarchical clustering using the Sørensen coefficient is an agglomerative approach that treats each observation as its own cluster. It then merges the most comparable groups until all data is combined into a single group. At each step, the method calculates Sørensen coefficients for all pairs of groups and then merges the groups with the highest coefficient. The generated dendrogram shows the connections created at each stage. The size of the link shows the difference between the merged groups, determined by the Sørensen coefficient. When forming groups, the clustering algorithm (or amalgamation) ensures the highest similarity possible for entities within a group, while the entities included in other groups show the highest dissimilarity possible towards the former. The codes under the Smart manufacturing category were first clustered with the codes under the Strategy category, and then with the codes under the Performance category. This approach allowed for a better understanding of how corporate communication links artificial intelligence, digitalisation, cloud, computing, and all the other terms under the smart manufacturing concept to strategic approaches and business performance separately. In the meantime, this process avoids the significantly high connections between codes under Strategy and Performance in the cases. An aspect of our approach that may generate uncertainty is the decision to use a single coding step. Due to the formal structure and standardisation of the annual reports of companies listed in the United States, we believe that the information is presented in a uniform and clear manner and, therefore, a potential parallel coding would result in similar code lists. The final code list was composed through reviews of the keywords identified by QDA Miner, a step taken to prevent the occurrence of terms or phrases that are not relevant in the context of this study.

The cluster analysis based on co-occurrences is complemented by several analyses. First, we perform a link analysis which allows for an improved visualisation of the connections between various codes. The objective of the link analysis is to identify connections between codes within a data set, complemented with weights or strengths of these connections (Olson and Lauhoff, 2019). Second, we have generated proximity plots for various pairs of codes, which are graphical representations of the distance between codes. In these plots, the distance (based on Sørensen's coefficient) from a code to the other codes is displayed on a single axis, thus facilitating the comparison between codes. A higher distance in the plot shows a greater similarity between codes. More details on these analyses are provided in the Results section. The possibility of distorting the results due to the outliers that sometimes result from random groupings of keywords, a problem that becomes more difficult to remedy in the case of small samples, as well as the appearance of the 'reversal' phenomenon (Xu and Wunsch, 2005) represents a disadvantage of the applied cluster analysis. Furthermore, the degree of confidence that can be placed in a content analysis is limited, since the contribution of the researchers who carried it out is impossible to replicate exactly. Even if the methodology can be reproduced consistently, this does not guarantee that the data used reflects reality and the results obtained are valid (Krippendorff, 2019). Qualitative analysis often restricts the generalisation of results to a larger sample of the population due to the subjective nature of the resources used and the involvement of the researcher in their processing. There is always

the possibility that the results produced will depend on the context from which the data was extracted. In such a situation, both the transparency and the researcher's position towards the subject must be clarified, the researcher himself becoming an important instrument of the analysis (Raskind et al., 2018).

### 3. Results and discussion

#### 3.1. Analysis of codes' frequencies

Figure no. 1 shows the distribution of codes in total codes (left) and in total number of cases (right) – detailed statistics of codes are available from the authors. The codes pertaining to the Smart manufacturing category are present in six to 89 paragraphs (0.3 to 4.3% of the total paragraphs); the most frequent code is 'Robots and automation', followed by 'Cybersecurity' and 'Sensors'. While 'Cybersecurity' is found in all cases, the other codes are encountered in four to 13 cases. For what concerns the Strategy category, the codes are present in 39 to 266 paragraphs (2.2% to 15.3% of total paragraphs); the code with the highest frequency is 'Competitive advantage', present in 266 paragraphs or 15.3% of total, and 'Research and development', identified in 162 paragraphs or 9.3% of the total paragraphs. Three codes under this category ('Competitive advantage', 'Research and development', and 'Innovation') are found in all annual reports, while the remaining two codes are included in 60-70% of cases. In the case of the Performance category, the code with the highest frequency is, by far, 'Growth', who is present in 365 paragraphs or 21% of total paragraphs, and in all cases. This is also the code with the highest frequency of all codes. 'Profitability' is also a code with a significant presence – 150 paragraphs or 8.6% of total paragraphs, and 100% of cases -, followed by 'Efficiency', who is encountered in 127 paragraphs (7.3%), and 100% of cases.

Across the three categories, Performance codes are present in 8.6% of paragraphs, on average, followed by Strategy codes (7.3% of paragraphs) and Smart manufacturing codes (2.3% of paragraphs). It is also noteworthy that several codes in the Smart manufacturing category – 'Cybersecurity', 'Sensors' and 'Robots and automation' - have higher frequencies in total paragraphs compared to some codes in the Strategy or Performance categories ('Product development', 'Differentiation', 'Agility'), which signals the substantial interest of these companies in upgrading their processes, products, production lines, and services to customers in the technological developments in the Industry 4.0 framework. It is worth mentioning that higher frequencies in of the codes are not only desired because they corroborate entrepreneurial interest in smart manufacturing, but because they increase the reliability of the coding process (Balluchi et al., 2021). It should be further highlighted that the prevalence of codes such as 'Robots and automation', 'Cybersecurity', and 'Sensors' underscores a substantial focus on technological advancements in manufacturing processes, supporting previous results (Zheng et al., 2021) with 'Cybersecurity' notably found in all cases, as mentioned earlier. Furthermore, we notice that the higher frequency of specific Smart manufacturing codes compared to select Strategy or Performance category codes signifies a pronounced interest among companies in leveraging Industry 4.0 technologies to enhance their operational efficiency, product development, and customer service, thus reinforcing the industry's commitment to technological integration and advancement (Bai et al., 2020).

We argue that the drawn observations not only emphasise the evolving landscape of industrial practices but also accentuate the strategic prioritisation of technology-driven innovation and performance enhancement strategies across the examined companies, aligning with and

contributing to the ongoing discourse in the contemporary literature on Industry 4.0 and strategic management practices within the manufacturing sector.

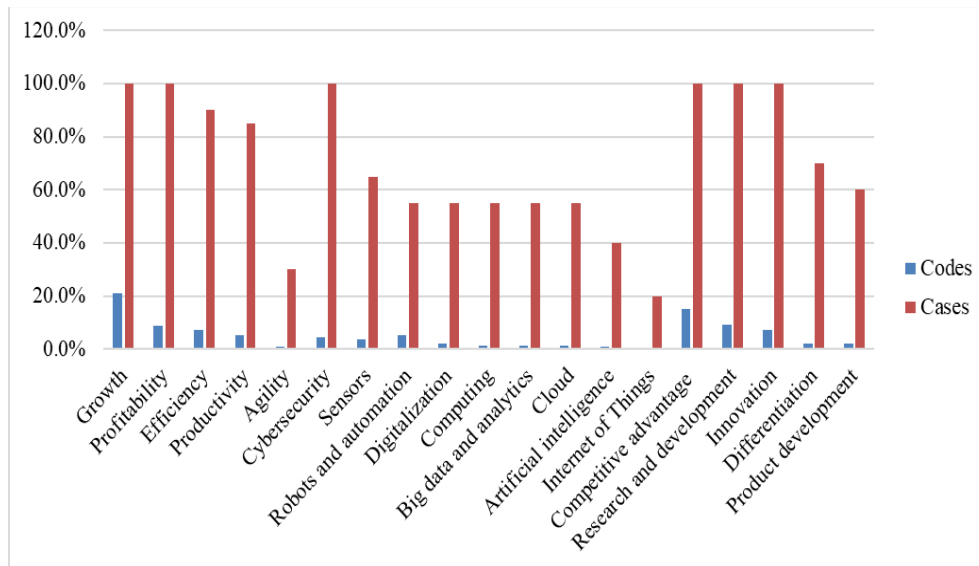


Figure no. 1. Codes frequencies in total codes and number of cases

### 3.2. Link and proximity analysis

The second stage of our investigation consists of identifying connections between codes and categories of codes, in the form of code co-occurrences and code similarity, with the help of link and proximity analysis. While the link analysis permits the identification of clusters between codes based on co-occurrences and similarity, the proximity analysis offers an individual and comparative perspective on codes and their connections.

Figure no. 2 shows the clusters formed between the 19 codes, based on the SC, as defined in equation (1) – as a measure of similarity between codes. The higher the value of SC, the higher the co-occurrence or similarity between the codes. The values of SC indicate 6 clusters, each with a different colour. The frequency of each code is displayed in the left part of the figure.

The SC for the codes vary between 1.000 (‘Profitability’-‘Research and development’-‘Innovation’-‘Growth’-‘Cybersecurity’-‘Competitive advantage’), suggesting a very high similarity between them, and 0.320 (‘Internet of Things’), indicating the lowest similarity with the other codes. We find the clustering of ‘Cybersecurity’ with the most frequent codes from the Strategy and Performance interesting, which highlights the increased relevance of cyberattacks for business performance, as well as the significant interest of corporate managers in protecting operations from undesired computer and security breaches.

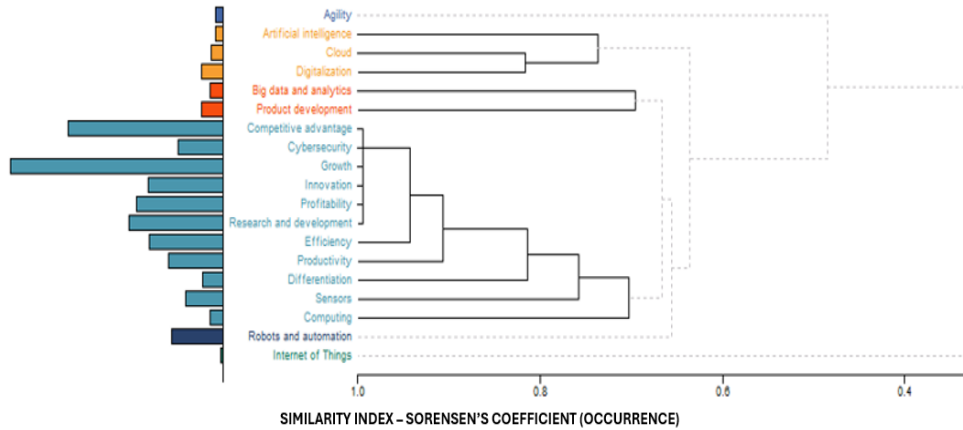


Figure no. 2. Links between codes identified by cluster analysis

At the same time, ‘Sensors’ and ‘Computing’ are integrated in the main cluster, suggesting that companies see them as major performance and strategic contributors to corporate success. ‘Artificial intelligence’, ‘Cloud’ and ‘Digitalisation’ are clustered together, with high SC ranging between 0.737 and 0.818, indicating similar corporate approaches to integrating and managing them in business operations. Also, ‘Big data and analytics’ and ‘Product development’ display a high SC which includes them in the same cluster (0.696).

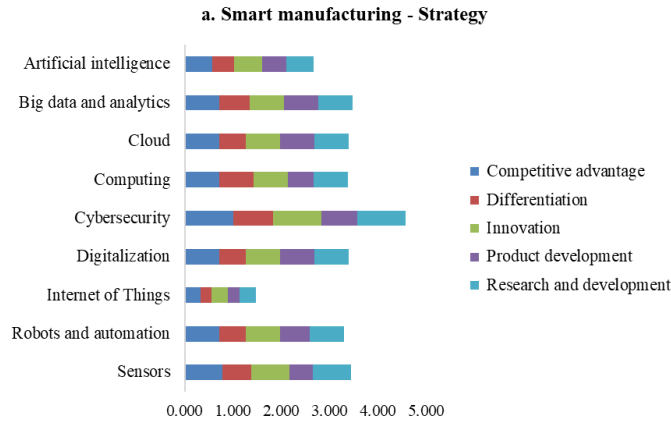
Figure no. 3 presents the similarity coefficients (SC) between all codes in a matrix format. The cells highlighted in blue show higher similarity between codes, the ones in red lower similarity, and the cells in white indicate medium similarity. Several codes under the smart manufacturing category exhibit increased similarity with Strategy and Performance codes: ‘Computing’ shows an SC of 0.759 with ‘Efficiency’; ‘Cybersecurity’ has SCs of 0.824 with ‘Differentiation’, 0.947 with ‘Efficiency’, 1.00 with ‘Growth’ and ‘Innovation’, ‘Productivity’, ‘Research and development’, and 0.919 with ‘Productivity’; ‘Sensors’ has an SC of 0.788 with ‘Competitive advantage’, of 0.774 with ‘Efficiency’ and 0.788 with each ‘Growth’, ‘Innovation’, ‘Profitability’ and ‘Research and development’.

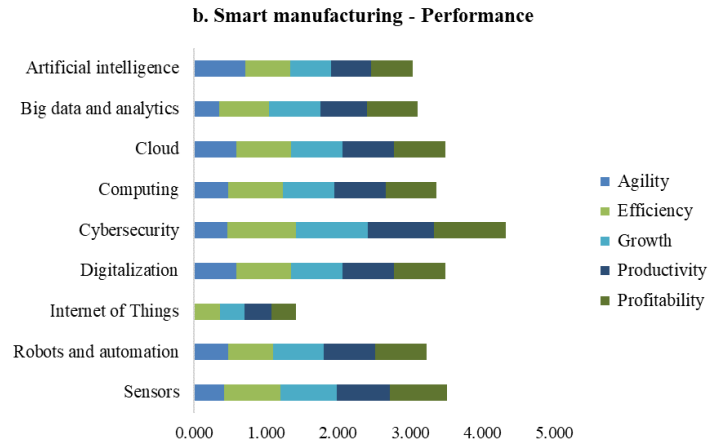
Within the Smart manufacturing category, ‘Cybersecurity’ is the most linked code to both Strategy and Performance codes, with an average SC of 0.915 with Strategy and 0.866 with Performance. For the Smart manufacturing – Strategy connections, ‘Big data and analytics’ displays an average SC of 0.693 with codes in Strategy, followed by ‘Sensors’ (SC of 0.687). The least linked codes under Smart manufacturing with Strategy are ‘Internet of Things’ (average SC of 0.294) and ‘Artificial intelligence’ (average SC of 0.534). In the case of Smart manufacturing – Performance links, ‘Sensors’, ‘Cloud’ and ‘Digitalisation’ show high average SCs of 0.701, 0.696 and 0.696 respectively. At the other end, ‘Internet of Things’ has the lowest average SC with the Performance category, 0.282. Across codes and categories, the average SCs are very similar, 0.646 for the Smart manufacturing – Strategy connection and 0.643 for the Smart manufacturing – Performance connection, confirming that large industrial corporations see both their business success and strategic choices inter-related with technological developments led by AI and digitalisation.

	Agility	Artificial intelligence	Big data and analytics	Cloud	Competitive advantage	Computing	Cybersecurity	Differentiation	Digitalization	Efficiency	Growth	Innovation	Internet of Things	Product development	Productivity	Profitability	Research and development	Robots and automation	Sensors
Agility	1.000	0.714	0.353	0.588	0.462	0.471	0.462	0.500	0.588	0.500	0.462	0.462	0.000	0.444	0.348	0.462	0.462	0.471	0.421
Artificial intelligence	0.714	1.000	0.526	0.737	0.571	0.526	0.571	0.455	0.737	0.615	0.571	0.571	0.333	0.500	0.560	0.571	0.571	0.632	0.476
Big data and analytics	0.353	0.526	1.000	0.545	0.710	0.455	0.710	0.640	0.727	0.690	0.710	0.710	0.267	0.696	0.643	0.710	0.710	0.636	0.417
Cloud	0.588	0.737	0.545	1.000	0.710	0.545	0.710	0.560	0.818	0.759	0.710	0.710	0.533	0.696	0.714	0.710	0.710	0.636	0.667
Competitive advantage	0.462	0.571	0.710	0.710	1.000	0.710	1.000	0.824	0.710	0.947	1.000	1.000	0.333	0.750	0.919	1.000	1.000	0.710	0.788
Computing	0.471	0.526	0.455	0.545	0.710	1.000	0.710	0.720	0.545	0.759	0.710	0.710	0.267	0.522	0.714	0.710	0.710	0.455	0.583
Cybersecurity	0.462	0.571	0.710	0.710	1.000	0.710	1.000	0.824	0.710	0.947	1.000	1.000	0.333	0.750	0.919	1.000	1.000	0.710	0.788
Differentiation	0.500	0.455	0.640	0.560	0.824	0.720	0.824	1.000	0.560	0.813	0.824	0.824	0.222	0.615	0.774	0.824	0.824	0.560	0.593
Digitalization	0.588	0.737	0.727	0.818	0.710	0.545	0.710	0.560	1.000	0.759	0.710	0.710	0.400	0.696	0.714	0.710	0.710	0.636	0.667
Efficiency	0.500	0.615	0.690	0.759	0.947	0.759	0.947	0.813	0.759	1.000	0.947	0.947	0.364	0.733	0.857	0.947	0.947	0.621	0.774
Growth	0.462	0.571	0.710	0.710	1.000	0.710	1.000	0.824	0.710	0.947	1.000	1.000	0.333	0.750	0.919	1.000	1.000	0.710	0.788
Innovation	0.462	0.571	0.710	0.710	1.000	0.710	1.000	0.824	0.710	0.947	1.000	1.000	0.333	0.750	0.919	1.000	1.000	0.710	0.788
Internet of Things	0.000	0.333	0.267	0.533	0.333	0.267	0.333	0.222	0.400	0.364	0.333	0.333	1.000	0.250	0.381	0.333	0.333	0.267	0.471
Product development	0.444	0.500	0.696	0.696	0.750	0.522	0.750	0.615	0.696	0.733	0.750	0.750	0.250	1.000	0.690	0.750	0.750	0.609	0.480
Productivity	0.348	0.560	0.643	0.714	0.919	0.714	0.919	0.774	0.714	0.857	0.919	0.919	0.381	0.690	1.000	0.919	0.919	0.714	0.733
Profitability	0.462	0.571	0.710	0.710	1.000	0.710	1.000	0.824	0.710	0.947	1.000	1.000	0.333	0.750	0.919	1.000	1.000	0.710	0.788
Research and development	0.462	0.571	0.710	0.710	1.000	0.710	1.000	0.824	0.710	0.947	1.000	1.000	0.333	0.750	0.919	1.000	1.000	0.710	0.788
Robots and automation	0.471	0.632	0.636	0.636	0.710	0.455	0.710	0.560	0.636	0.621	0.710	0.710	0.267	0.609	0.714	0.710	0.710	1.000	0.667
Sensors	0.421	0.476	0.417	0.667	0.788	0.583	0.788	0.593	0.667	0.774	0.788	0.788	0.471	0.480	0.733	0.788	0.788	0.667	1.000

Figure no. 3. Link analysis – the matrix perspective

A combined individual and comparative perspective on code similarity is presented in figure no. 4, which shows the SC for each code in the Smart manufacturing category and the respective codes in the Strategy and Performance categories. As previously identified, ‘Cybersecurity’ has the strongest link with all the codes in the Strategy and Performance categories combined, reaching a cumulative SC of 8.902 (4.574 for Strategy and 4.328 for Performance). The next codes in terms of cumulative SC are ‘Cloud’ and ‘Digitalisation’ with 6.867, while the last code is ‘Internet of Things’ with a cumulative SC of only 2.882.





**Figure no. 4. Proximity analysis**

In individual comparisons, several observations are notable. First, except for ‘Agility’, ‘Cybersecurity’ beats all the other Smart manufacturing codes in relation to Strategy and Performance codes, showing its pervasive influence on business preservation and success. Second, ‘Artificial intelligence’ displays the strongest connection to ‘Agility’ of all Smart manufacturing codes, followed by ‘Cloud’ and ‘Digitalisation’; this points toward the use of these smart manufacturing tools to leverage their capabilities and build supplier, more flexible, and resilient operations. Third, there is no connection between ‘Internet of Things’ and ‘Agility’, which may signal that to achieve swiftness in operations firms need to go beyond using the Internet and implement more advanced smart manufacturing tools, such as cloud computing, AI, robots, sensors, etc. Fourth, all Smart manufacturing codes are linked to all codes under Strategy and Performance, indicating the strong intertwining of technological advancements, strategic priorities, and performance framework in the Industrial sector.

Overall, these findings align with previous literature that emphasises the intertwined nature of technological advancements, strategic priorities, and performance frameworks within the industrial sector (Dos Santos et al., 2021). The substantial correlations among specific codes highlight the growing significance of cybersecurity, advanced computing, and sensor technologies in shaping corporate strategies and enhancing performance (Kalsoom et al., 2020; Rosin et al., 2022). Additionally, the nuanced connections between Smart manufacturing codes and Strategy or Performance categories underscore the intricate relationship between technological advancements and strategic decision-making in the pursuit of operational excellence and competitive advantage, resonating with established literature on Industry 4.0 and strategic management practices.

**Conclusions**

This study delves into the annual reports of the 20 largest global companies in the industrial sector listed on US stock exchanges, aiming to understand the thematic nuances and interconnectedness between smart manufacturing, business strategy, and corporate performance within these corporate narratives. Employing qualitative data analysis software,

these reports have been meticulously analysed and distinct themes have been identified along with associated codes to uncover the underlying patterns and correlations. The analysis offered a panoramic view encompassing business overviews, risk factors, market analyses, audited financial statements, and detailed management discussions, setting the stage for a comprehensive understanding of these corporations' operations.

Notable findings reveal that while Smart manufacturing codes were less frequent than Strategy or Performance codes, specific technologies such as 'Robots and automation,' 'Cybersecurity,' and 'Sensors' exhibited higher frequencies, underscoring the emphasis on integrating Industry 4.0 technologies. Particularly, 'Cybersecurity' was omnipresent across all cases, reflecting an escalating concern about safeguarding operations against threats. Cluster analysis revealed distinctive groupings of codes, with a key cluster emerging around 'Cybersecurity' interlinked with Strategy and Performance codes. This underscores the increasing relevance of cybersecurity in the shaping of business performance strategies, as evidenced by annual report excerpts emphasising potential cyber incident impacts across operations. Moreover, 'Cybersecurity' emerges as the most strongly connected code to Strategy and Performance categories, highlighting its pervasive influence. While 'Artificial intelligence,' 'Cloud', and 'Digitalisation' display robust Strategy and Performance connections, 'Internet of Things' lacks a clear 'Agility' link, signaling the need for more advanced smart manufacturing tools to achieve operational nimbleness. The nuanced connections accentuate the intricate relationship between technological integration and strategic decision-making in pursuing operational excellence and a competitive edge.

Overall, we maintain that the comprehensive analysis performed in this research underscores the evolving landscape of industrial practices, emphasising a strategic focus on technology-driven innovation and performance enhancement. The observed correlations illuminate the profound impact of Industry 4.0 technologies on shaping strategic priorities, performance narratives, and operational strategies within the manufacturing sector. In turn, these insights provide valuable cues for practitioners and researchers alike, emphasising the imperative of integrating technological advancements with strategic objectives to navigate the increasingly complex industrial landscape. Moreover, we argue that the study's reliance on a qualitative data analysis tool for the exploration of annual reports, despite its inherent advantages and limitations, has unveiled layers of qualitative information that might have been challenging to uncover through traditional methods alone. In essence, this research contributes to the existing discourse by shedding light on the intertwined nature of Smart manufacturing concepts, strategic imperatives, and performance frameworks within the manufacturing sector, emphasising the pivotal role of technology-driven innovation in fostering operational excellence and competitive advantage among these industry leaders.

This study relied solely on annual reports which provide an incomplete picture of smart manufacturing adoption. Future research should incorporate other data sources such as surveys, interviews, and third-party technology audits. The sample was limited to large US industrial firms, so exploring smaller manufacturers and international contexts could reveal different technology integration patterns. Moreover, future studies can address other factors impacting adoption such as investments, capabilities, and culture. Additionally, future works could apply mixed methods that combine text mining with statistical analysis to uncover relationships between technology integration maturity, costs, strategic priorities, and performance metrics. The limitations imposed by a qualitative content analysis regarding the validity of the results and the reliability of the digital-assisted coding process must also be

considered in the interpretation of the results. Finally, the existence of a wide variety of clustering procedures opens up the possibility of approaching a similar topic to that of our work using other methods such as BIRCH and CURE, which address the problems presented by the processing of large samples and the presence of outliers, respectively, and allow the formation of clusters with more complex structures.

### Disclaimer

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