https://doi.org/10.62836/emi.v3i4.243
Global Science Publishing

EMI
Economics & Management Information
https://ojs.sgsci.org/journals/emi

Article

Enhancing Industrial Management through AI Integration: A Comprehensive Review of Risk Assessment, Machine Learning Applications, and Data-Driven Strategies

Tian Tian [1,*], Sihan Jia [2], Jindi Lin [3], Zichen Huang[3], Kei O Wang [3] and Yubing Tang [4]

[1] *Stuart Business School, Illinois Institute of Technology, Chicago, IL60661, USA*
[2] *Mathematics and Statistics, Georgia State University, Atlanta, GA30303, USA*
[3] *University of Illinois Urbana-Champaign, Urbana, IL61801, USA*
[4] *Stuart Business School, Illinois Institute of Technology, Chicago, IL60661, USA*

Abstract: This research investigates the transformative potential of integrating artificial intelligence (AI) with comprehensive risk management frameworks in industrial management. While AI applications have advanced in industrial settings, there is a lack of studies that fully integrate AI with macro risk factors such as PESTLE (political, economic, social, technological, legal, and environmental) and ESG (environmental, social, and governance) factors. These factors, often rooted in human activities and decisions, are critical to understanding and mitigating risks in complex industrial environments. By incorporating AI methods, such as machine learning and deep neural networks, organizations can enhance their ability to identify, analyze, and mitigate these risks efficiently. Recent developments, including OpenAI's language models, further strengthen this approach by enabling large-scale data analysis and supporting real-time risk assessment and decision-making. OpenAI's tools can interpret vast volumes of regulatory, economic, and social data, providing valuable insights to decision-makers. This research underscores the innovative potential of AI-driven risk management to enhance the stability and resilience of industrial management. By reducing human error and adapting to dynamic risk factors, this integration offers a forward-looking strategy for optimizing performance, ensuring operational excellence, and supporting sustainable practices across sectors.

Keywords: risk factors; PESTLE; ESG; AI; OpenAI; industrial management

1. Introduction

Industrial management plays a critical role in enhancing productivity, reducing costs, and promoting sustainability across multiple sectors. With the integration of artificial intelligence (AI) technologies, the potential for transformative improvements in industrial management is vast. This article provides a comprehensive review of AI-driven techniques that support risk assessment, operational efficiency, and data-driven strategies within industrial management. In addition, it examines the associated challenges, risks, and future directions of AI integration within this evolving field.

Received: 14 October 2024; Accepted: 8 November 2024.

* Corresponding: Tian Tian (ttian4@hawk.iit.edu)

1.1. Importance and Scope of Industrial Management

Industrial management is widely recognized as a high-risk field encompassing diverse activities, from project planning and operations to maintenance and investment. It involves a structured approach to optimizing organizational processes, improving customer service, and creating business value across industries [1,2]. While crucial to the success of industries like construction, manufacturing, and logistics, industrial management requires frameworks that address project complexities, cost uncertainties, and scheduling risks [3]. Effective management practices play a pivotal role in mitigating these challenges by standardizing scope validation, risk assessment, and change management processes throughout the project life cycle [4,5].

1.2. Challenges and Risk Factors in Industrial Management

The high-risk nature of industrial management involves numerous challenges. Common issues include scope creep, budget overruns, and project delays due to expanding project boundaries or unanticipated factors. Industrial management must address these risks by encompassing essential processes such as conceptual development, scope statement, work authorization, reporting, control systems, and project closeout [6]. While various standards and guidelines exist, there is no universally applicable methodology, making adaptability essential for managing unique project demands and mitigating risks across diverse industries [7–9]. Effective risk management frameworks, such as PESTLE (political, economic, social, technological, legal, and environmental) and ESG (environmental, social, and governance), help in comprehensively assessing both external and internal factors affecting industrial operations [10].

1.3. The Role of AI in Enhancing Industrial Management

Artificial intelligence, particularly Machine Learning (ML), Deep Learning (DL) and OpenAI, is gaining recognition for its applications in industrial management. AI has shown significant potential in areas such as financial management, risk prediction, safety monitoring, and productivity estimation, offering insights that assist investors, optimize decision-making, and improve safety [11, 12]. However, despite AI's recognition in frameworks like the Gartner Hype Cycle for Emerging Technologies, its application in industrial management remains underexplored. Integrating AI methodologies can enable advanced risk assessment and automate complex decision-making processes, helping managers reduce human error and better address high-risk aspects of industrial management [5,13].

1.4. Structure of the Paper

This paper provides a comprehensive overview of AI integration in industrial management. Section 2 explores various risk factors, including PESTLE and ESG, covering areas such as process design, quality control, equipment and technology, environmental impact, supply chain management, and safety and risk management. Section 3 examines AI methods as well as OpenAI, focusing on the challenges, current applications, and future potential of AI in supporting risk management and operational optimization. Finally, Section 4 concludes the research, highlighting how AI integration and structured risk frameworks can significantly advance industrial management practices, promoting safer, more efficient, and adaptable operations [14,15].

Overall, this research addresses the scarcity of literature on combining risk factors and AI to enhance industrial management across various sectors. The integration of these elements can pave the way for significant advancements in industrial management, minimizing risks and optimizing outcomes. This review highlights the potential of AI and structured risk frameworks in transforming industrial management practices, contributing to safer, more efficient, and more adaptable operations [16–18].

2. Challenges

This section addresses current challenges in industrial management, recognizing that accurately identifying and categorizing risks across diverse processes remains an area for improvement in achieving effective risk assessment and mitigation across projects.

2.1. Current Problems of Risk Assessment

Different researchers [19–22] have stated that organizational dynamics and multidisciplinary characteristics of the business environment can work as standards to label most risks. However, the network of project processing elements of uncertainty and risk distribution is broadened because of the current multi-stakeholder-based business environment [23 – 25]. Under these circumstances, the challenge of risk process management using heavy machine products, as the example shown in Figure 1 is not understanding the cause of any uncertainty [26] and identifying how to understand the cause of any delay [27]—but identifying all types of risks with a certain probability over the whole project process.

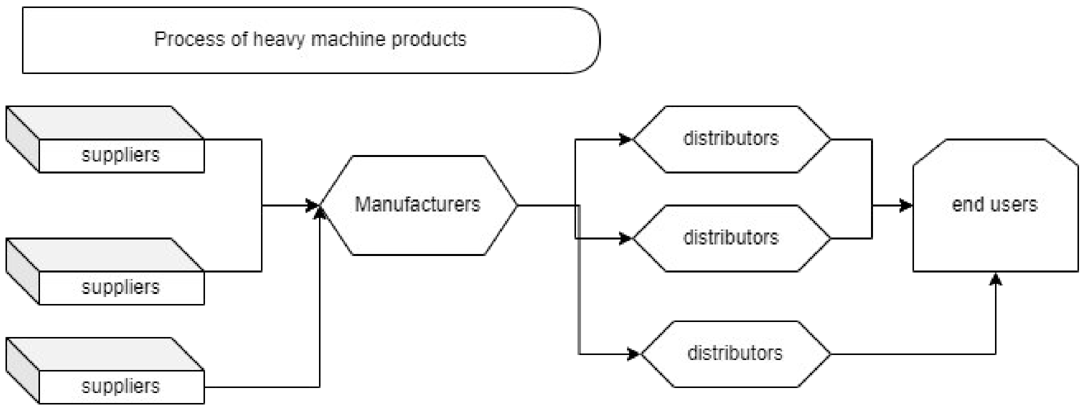

Figure 1. An example of process management in heavy machine products.

Currently, most existing risk identification or classification methods need more source-oriented groupings for precise risk exposure [28]. In addition, Harvest [29] stated that a significantly large number of projects often fail due to the increases in project complexity over time. Such complexity makes identified risks in different projects do not have the same or similar weight to impact all projects [30,31].

Possible risks in process management, which are difficult to identify a certain probability over the whole project process and are the crucial part of assessing risks, are listed below:

Lack of standardization: Inconsistent processes [32] can lead to inefficiencies, errors, and decreased productivity. B. Münstermann proposed that business process standardization (BPS) could positively impact business process performance, serving as a driver of process success. Through empirical analysis of data from 156 firms, the study finds that BPS significantly impacts process performance, particularly in terms of time, cost, and quality, emphasizing its importance as a vital tool in a firm's BPM toolbox and highlighting the need to consider process standardization in both research and management of business processes [33].

Poor quality control: Lack of proper checks and controls [34, 35] can result in lower-quality outputs. B. Klefsjö highlighted the perspective of Six Sigma as a methodology for total quality management. The paper emphasized the integration of Six Sigma principles into various quality management practices to enhance organizational performance and achieve higher levels of quality control [36].

Resistance to change: Employees may resist changes [37, 38] to established processes, making process improvement initiatives difficult to implement. A. Vas challenges the traditional view that resistance to change is irrational and solely originates from low-level employees. Through an in-depth case study of a telecommunications company, the research reveals that both implicit and explicit resistance exists at all levels of the organization, highlighting the critical role of middle managers in facilitating strategic organizational change [39]

nadequate resources: Limited resources, including budget, personnel, and technology [40], can impede process improvement and innovation. M. Arias. et al. presented a systematic mapping study on human resource allocation in business process management (BPM) and process mining. The findings highlighted the evolving nature of this research area, where new recommendations are applied to real case studies, and the need for further validation and evaluation through simulations and case studies [41].

Business disruptions: Unplanned events such as natural disasters or pandemics can disrupt processes and negatively impact operations [42]. M.A. Cohen et al. provided a comprehensive review of Paul Kleindorfer's contributions to operations management, focusing on his risk management research. Kleindorfer proposed various topics including optimal control theory, decision science, investment planning, and supply chain risk to maintain sustainable operations and develop contract and risk hedging frameworks in supply management [43].

2.2. Identify Risk Factors of Macro and Quality Dimensions

In industrial management, effective risk management requires identifying and categorizing risk factors across both macro and quality dimensions, with an increasing emphasis on Environmental, Social, and Governance (ESG) considerations. ESG factors provide a framework for assessing an organization's impact on the environment, social stakeholders, and governance structures, which is essential for aligning industrial operations with evolving stakeholder expectations and regulatory demands. By integrating ESG with structured frameworks like PESTEL, organizations can gain a comprehensive understanding of the external and internal elements influencing their business environment.

This section provides an integrated review of relevant research related to industrial management, exploring how PESTEL and ESG analysis can aid in identifying and managing these diverse risk factors. Through this approach, businesses can assess potential impacts on productivity, operational stability, and market positioning and develop appropriate strategies for risk mitigation. Leveraging these frameworks enables organizations to proactively manage risks in both macro and quality dimensions, thereby enhancing resilience, optimizing outcomes, and fostering sustainable growth within industrial management practices.

2.2.1. PESTEL Risk Factors

When it comes to risk management in industrial processes, there are various risk factors that can be categorized into macro and quality dimensions. By considering the PESTEL elements, it becomes possible to identify risk factors in both macro and quality dimensions. The PESTEL framework provides a structured approach to understanding the external factors impacting a business environment, enabling organizations to assess risks and develop appropriate strategies for risk management. Numerous studies have highlighted the significance of political, design, and economic risks in various industries [44]. Figure 2 illustrates the elements of PESTEL analysis, including Political, Economic, Social, Technological, Environmental, and Legal factors, which are strategic factors used to evaluate the business environment of a firm.

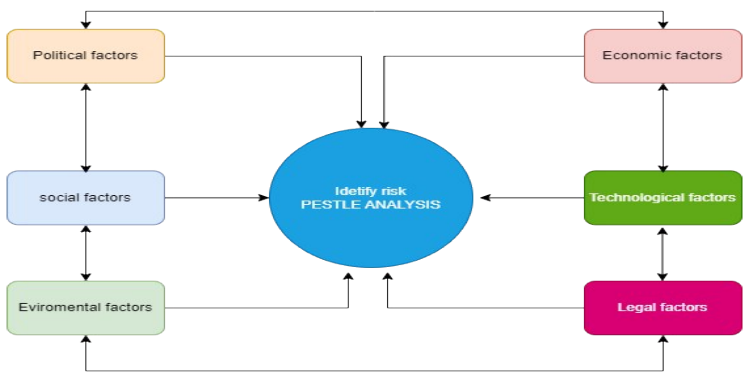

Figure 2. PESTEL Risk Factors.

Political Factors: Political factors encompass government regulations, policies, and stability. Changes in political landscapes or shifts in government priorities can impact industrial processes through new regulations or policy changes. Political risks [45] pose uncertain financing and often lead to a potential revenue decline. Industries such as construction, manufacturing, and heavy machinery operate in nations with distinct political issues. The growing tensions and instabilities in the global political climate, particularly national rivalries [46–48], can impact business growth and limit market expansion.

Economic Factors: Economic risk factors encompass the determination of aggregate demand and aggregate investment in an economy, influenced by macroeconomic factors such as inflation rate, savings rate, interest rate, foreign exchange rate, and economic cycle. Micro-environmental elements [49], such as competition standards, affect the industry's competitive advantage [50]. The economic downturn following COVID-19 will present several challenges to market players as customers' purchasing power is affected [51].

Social Factors: Social factors consider societal attitudes, demographics, cultural norms, and consumer behavior. Shifts in social trends or consumer preferences can impact industrial processes, such as the socioeconomic trend of improving wealth distribution [52] expands people's purchasing power. However, describing employment and earnings within the industry is complex [53].

Technological Factors: Technological factors involve advancements and innovations in technology that can impact industrial processes, such as the Internet of Things (IoT) [54] and AI, which can deliver the required level of effectiveness for sustaining a high return on investment in supply-chain systems. Automation, artificial intelligence, and machine learning continuously enhance supply chain systems [55].

Environmental Factors: Environmental factors consider industrial processes' ecological aspects and sustainability [56]. Risks related to environmental factors include climate change impacts, resource scarcity, pollution, and environmental regulations. Failure to address these risks can lead to reputational damage and legal consequences [57].

Legal Factors: Legal factors come into play for industries operating in challenging environments governed by distribution legislation [58], such as manufacturing, construction, and heavy machinery. Businesses also encounter challenges related to economic crime or fraud, navigating the regulatory landscape in their home nation and every jurisdiction where they conduct business.

By utilizing the PESTEL framework, organizations can systematically analyze and understand the various risk factors associated with macro dimensions (external factors) and quality dimensions (internal factors). This comprehensive approach enables proactive risk management and allows organizations to develop strategies to mitigate, monitor, and respond to these risks effectively.

2.2.2. ESG Risk Factors

In industrial management, Environmental, Social, and Governance (ESG) risk factors are crucial for assessing an organization's impact and resilience. Integrating ESG considerations into industrial management practices allows organizations to evaluate risks associated with environmental impact, stakeholder relations, and governance structures. This approach provides valuable insights into operational vulnerabilities, enabling more sustainable decision-making. ESG risk data is increasingly important for understanding regulatory, reputational, and financial exposures, allowing organizations to address these risks proactively. As stakeholders and investors demand higher standards of transparency and accountability, ESG integration in industrial management helps align organizational goals with these expectations.

ESG risk factors focus on an organization's effect on the environment, its treatment of stakeholders (such as employees and communities), and its governance practices. Within industrial management, ESG data sheds light on potential risks and opportunities related to the organization's operations, products, and services [59-61]. By collecting and analyzing ESG risk data, companies can assess their exposure to various risks, including regulatory and reputational risks, which can influence financial performance [62,63]. This data-driven approach supports informed decision-making aimed at minimizing risks and enhancing ESG performance [64]. As investors increasingly consider ESG factors in their investment decisions, organizations are expected to demonstrate transparency and accountability in these areas.

However, collecting ESG risk data presents challenges. Data availability is often limited [65], particularly for smaller organizations or those operating in emerging markets, where data on ESG risks may be scarce. Additionally, data standardization is a significant challenge, as there is often inconsistency in how ESG data is collected and reported, complicating comparisons across organizations [66].

Despite these challenges, ESG risk data collection and analysis are becoming essential in industrial management. By proactively managing ESG risks, organizations can meet higher standards of transparency and accountability and align with stakeholder and investor expectations. Incorporating ESG data into industrial management enables organizations to identify areas for improvement, mitigate risks, and enhance overall performance regarding environmental impact, social responsibility, and governance practices.

2.3. Additional Risk Factors in Industrial Management

Beyond PESTEL and ESG factors, other key risk factors in industrial management include design, quality control [67], equipment and technology, environmental impact [68], supply chain management, and safety and risk management. Addressing these factors within industrial management frameworks is essential for achieving consistent outcomes, minimizing risks, and improving overall process performance. Effective risk management in these areas allows organizations to navigate uncertainties, reduce errors, and increase the likelihood of project success.

Process Design: Designing effective industrial processes requires a thorough understanding of physical and chemical principles [69]. Researchers may focus on factors such as material properties, reaction kinetics, and process optimization to develop efficient, cost-effective processes that align with industrial goals and regulatory standards.

Quality Control: Ensuring consistent product quality is essential in industrial management [70]. Researchers and practitioners use process monitoring, statistical process control, and quality assurance measures to maintain standards and identify areas for improvement, ensuring products meet predefined quality criteria [71–74].

Equipment and Technology: Industrial processes often rely on specialized equipment and advanced technologies [75,76]. Equipment reliability, maintenance requirements, and emerging technological advancements are key areas of focus for researchers and practitioners aiming to improve efficiency, reduce costs, and enhance operational resilience in industrial management.

Environmental Impact: Industrial processes can have significant environmental consequences, such as emissions, waste generation, and resource consumption [77, 78]. Industrial management increasingly considers environmental regulations, sustainability metrics, and life cycle analysis to assess and mitigate these impacts, promoting sustainable practices within organizations.

Supply Chain Management: Industrial processes are frequently integrated within a broader supply chain, where disruptions or inefficiencies can significantly affect process performance [79,80]. Researchers emphasize supplier relationships, logistics, and inventory management to identify and address potential risks, ensuring a seamless and resilient supply chain.

Safety and Risk Management: Industrial processes carry inherent safety risks, including potential for fires, explosions, and chemical spills. Effective industrial management requires hazard analysis, risk assessment, and emergency response planning to ensure safe operations and minimize accident risks [81,82].

Each of these risk factors plays a vital role in industrial management, and the relevance of specific factors depends on the industry and process context. By focusing on these dimensions, organizations can create robust industrial management practices that support resilience, enhance operational outcomes, and promote long-term success.

3. AI Techniques Used in Industrial Management

As industries undergo digital transformation, artificial intelligence (AI) is playing an increasingly vital role in enhancing industrial management practices. By integrating machine learning, data mining, natural language processing (NLP), and advanced predictive technologies, AI is helping organizations manage risks, optimize processes, and reduce costs across various sectors. This section reviews AI-driven methodologies tailored to industrial management, with a focus on improving safety, quality, and operational efficiency. Table 1. provides an overview of machine learning techniques and applications, illustrating diverse datasets, methods, and specific implementations across sectors such as construction, mining, manufacturing, and after-sales services.

3.1. Machine Learning-Driven Approaches

Machine learning (ML) technologies are becoming indispensable in many industries, including manufacturing [83–85] and healthcare [85,86], to address the challenges of digital transformation. (Table 1 summarizes methods used in industrial management.) Gartner has pointed out the expanding demand for ML, predicting that organizations expect to double the number of ML projects within a year [87]. However, while ML is gaining traction in machinery industries, its full adoption in heavy machinery and construction sectors remains limited [88,89].

In industrial management, ML approaches offer significant potential for reducing productivity risks by continuously optimizing interactions among employees, clients, and stakeholders. Technological investments [90,91] in ML can position the heavy machinery and construction sectors to stay competitive and profitable.

For instance, a study [92] (illustrated in Figure 3) showed that identifying risk factors and generating predictive models using ML could assist in managing industrial risks. The study identified key risk factors, including before-accident and after-accident conditions, and found that the Gradient Boosting model was the most effective in predicting critical risk events.

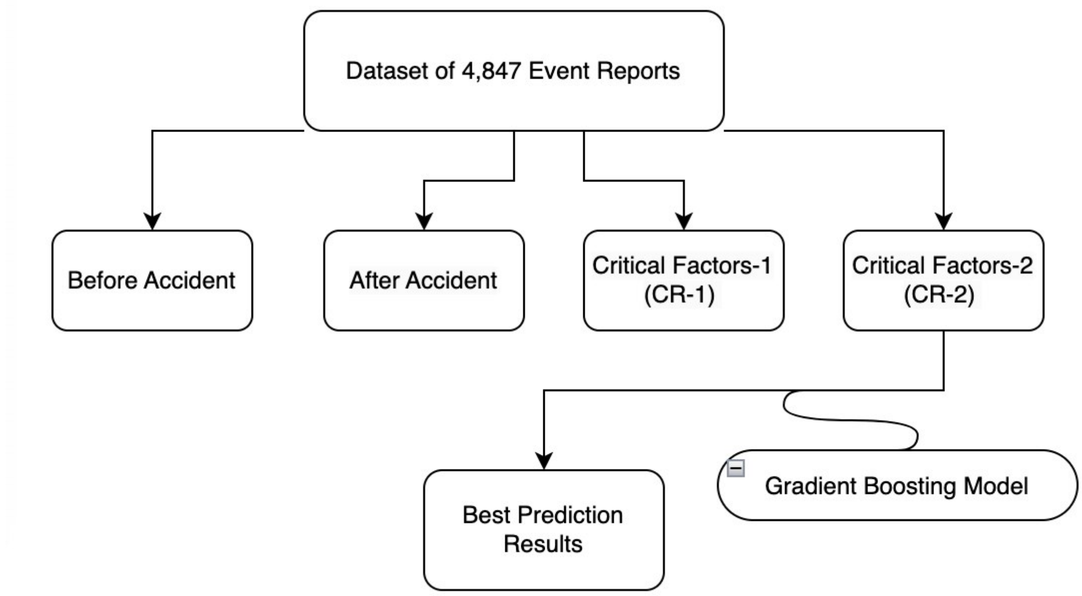

Figure 3. Flowchart of Study [93].

In another study [93], accident data from Singapore's construction industry was analyzed using neural networks, helping identify incidents and develop effective mitigation strategies. ML is proving valuable for stakeholders in predicting and reducing industrial risks. For example, a study [94] employed sequential minimal optimization for soft-margin support vector machines with n-fold cross-validation to assess constructability in technology projects, enabling accurate risk assessment for industrial management applications.

3.2. Data Mining and Collection Methodologies

Data mining and data collection are integral to managing macro risks in industrial management. However, there are challenges:

Data Availability: Reliable data to assess macro risks is often scarce, especially in emerging markets where access to ESG and operational data may be limited.

Data Privacy and Security: Protecting sensitive information is essential, as macro risk data can contain confidential elements that require secure handling.

Resource Constraints: Time, budget, and personnel limitations may impede effective data collection and analysis.

A survey of technology companies [95] revealed that 75–85% of ML projects do not meet expectations, mainly due to data and software quality issues [96]. The Cross-Industry Standard Process Model for Data Mining (CRISP-DM) [97-99] is frequently used to ensure consistency in industrial projects and is considered an ideal process model for industrial data mining [100, 101]. Applications of CRISP-DM are expanding across sectors, from quality diagnostics [102–104] to marketing [105], warranty management [106], and other industrial research areas.

CRISP-DM can serve as a framework [107] for exploring industrial data, such as safety records and incident reports, enabling organizations to conduct targeted interventions. For instance, random forest (RF) modeling has been employed for monthly safety performance projections, achieving an accuracy of 0.78.

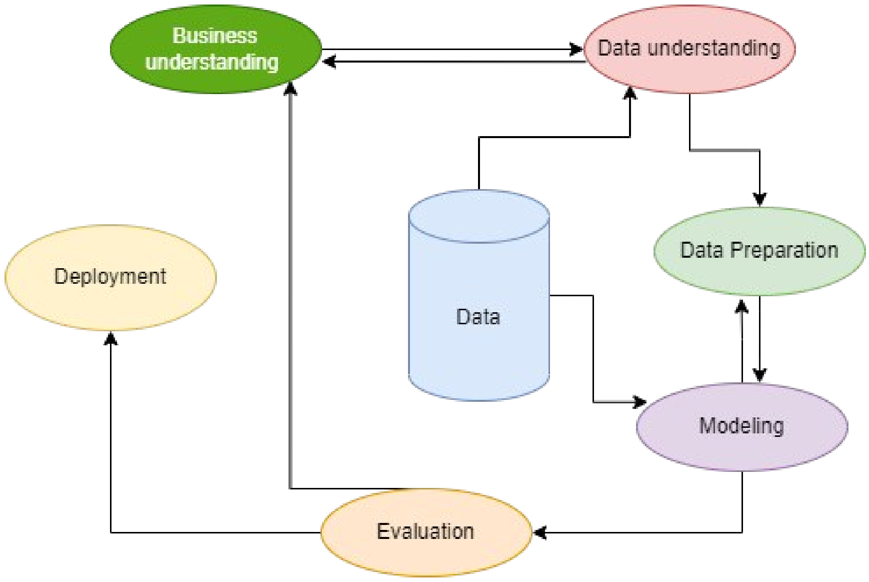

Figure 4. CRISP-DM construction.

Additional ML techniques, such as random under-sampling (RUS), random over-sampling (ROS), and synthetic minority over-sampling technique (SMOTE), have been used to predict industrial accidents, particularly in construction. Techniques like random forest (RF), Naïve Bayes (NB), K-Nearest Neighbor (KNN), and artificial neural networks (ANNs) enhance predictive accuracy, as shown in Figure 4.

3.3. Nlp Method Used For Accident Prediction By Extracting Textual Data

For accident prediction in NLP, machine learning algorithms such as decision trees, random forests, and support vector machines are commonly used. In addition, natural languages processing techniques such as sentiment analysis, text classification, and entity recognition are also utilized to extract relevant information from text data such as news articles or social media posts. The goal of these methods is to identify patterns and relationships between text data and accident occurrences and make predictions about potential accidents based on this analysis.

Aside from that, the NLP extracted textual construction injury reports with Natural Language Processing, featured them with attributes and categorical safety outcomes and then applied Random Forest (RF) and Stochastic Gradient Tree Boosting (SGTB) to the dataset. Due to the binary and physical Nature of the input variables, the outcomes can provide a reliable prediction of accidents.

3.4. Future Direction of AI Used to Reduce Risks Associated with Process Management

Human error is a significant contributor to many accidents and incidents in industrial processes, and AI can help to mitigate this risk in several ways:

Autonomous control: AI can be used to automate certain processes, reducing the need for human intervention and minimizing the risk of errors.

Intelligent decision support: AI can provide intelligent decision support to operators, helping them to make informed decisions and reducing the risk of errors.

Training and simulation: AI can create realistic training and simulation scenarios that allow operators to practice responding to various situations, reducing the risk of errors during real operations.

Monitoring and alerting: AI can continuously monitor process data and alert operators to potential issues, allowing them to take corrective action before an incident occurs.

Root cause analysis: In the event of an incident, AI can be used to perform root cause analysis to identify the underlying causes and help prevent similar incidents from occurring in the future.

L. Li et al. discussed the application of artificial intelligence (AI) in drinking water treatment (DWT) processes. By leveraging AI technology, the goal is to minimize human errors and improve efficiency in managing and operating DWT systems by realizing water quality diagnoses, autonomous decision-making, and operation process optimization based on data analysis and evolutionary learning mechanisms [108].

H. Khayyam et al. discovered that human error is the leading cause of automotive crashes. Therefore, AI and Internet of Things (IoT) technologies play an essential role in the development of fully autonomous vehicles by enabling the transformation by combining real-world and digital knowledge, reducing human errors, and increasing vehicle safety [109].

3.5. Leveraging OpenAI for Data-Driven Decision Making and Operational Efficiency in Industrial Management

OpenAI and other advanced AI technologies hold significant potential for enhancing industrial management by reducing risks and improving operational efficiency across several key areas:

Predictive Maintenance: AI can analyze data from sensors and other sources to identify patterns and predict when equipment is likely to fail, allowing for proactive maintenance. This predictive approach helps prevent costly downtime and safety incidents, enhancing equipment reliability and operational continuity in industrial settings.

Process Optimization: By analyzing large datasets and running simulations, AI identifies optimal operating conditions for various processes. This optimization reduces the likelihood of accidents and ensures consistent product quality, which is crucial for maintaining competitiveness and efficiency in industrial operations.

Fault Detection and Diagnosis: AI algorithms analyze real-time data from sensors to detect anomalies and diagnose faults quickly, enabling rapid responses to potential safety incidents or production losses. Fault detection minimizes downtime and maintains the integrity of industrial processes, contributing to overall resilience.

Safety Planning and Response: AI can simulate various operational scenarios, predicting potential safety incidents and identifying appropriate response measures. These insights allow industrial managers to prepare effective safety plans, mitigating risks to personnel and the environment.

Compliance: By continuously monitoring and analyzing operational data, AI helps ensure that processes adhere to regulatory standards, reducing the risk of fines, legal actions, and reputational damage. Automated compliance monitoring supports adherence to complex regulatory requirements and ensures sustainable operations.

In reviewing 500 case studies, S.L. Wamba-Taguimdje et al. found that AI aids in optimizing processes, enhancing automation, managing information, and transforming organizational outcomes. The study also highlights AI's capability to detect, predict, and engage interactively with various industrial processes, demonstrating its transformative impact on performance [110].

OpenAI's Contribution to Industrial Management: OpenAI's advanced AI technologies, including language models like ChatGPT, further support industrial management by facilitating complex data analysis and interpretation, offering valuable insights for decision-making. OpenAI's language models enable managers to recognize patterns, monitor trends, and assess potential risks, improving strategic and operational decisions. These tools assist in optimizing process design, quality control measures, supply chain management, and safety protocols, making operations more efficient and adaptable to changes [111,112].

Additionally, OpenAI's AI capabilities allow for automation and optimization across industrial processes, which reduces human errors, enhances productivity, and improves overall performance. With the integration of AI-driven analysis, data interpretation, and automation, OpenAI's technologies offer industrial managers the ability to reduce risk, improve safety and compliance, and achieve higher levels of productivity and sustainability [113]. By incorporating these capabilities, organizations in the industrial sector can reduce incidents, maintain compliance, and achieve operational excellence, improving both their safety and bottom line.

Table 1. Summary of Machine Learning Techniques and Applications in Industrial Management across Various Sectors.

Name/Reference	Environment	Summary and Specialty	Techniques		Dataset
			ML Methods	Theoretical Background	
Vineeth, V.S., Kusetogullari, H., & Boone, A. (2020, August) https://doi.org/10.1109/IS48319.2020.9200128	Python	- Machine Learning - Forecasting sales model for truck components in Volvo Trucks	- SVM - Ridge Regression - Gradient Boosting Regression - Random Forest Regression		- Historical sales data of truck components for a period of 24 months including information about the product type, the month of sales, and quantity sold
Sharma, P., Khater, S., & Vashisht, V. (2021, January) https://doi.org/10.1109/ICCAKM50778.2021.9357751	Python	- Machine Learning - Prediction of turnover of a company which is helpful for better understanding A17of market trends and stocks	- Linear regression - Random forest		- Data covered the sales data from 5 automotive companies in Indian market from 2019 to 2021
McClelland, J., & Rust, J. (2018) https://doi.org/10.1515/jbnst-2018-0023	Python	- Dynamic programming model - Estimate key relationships of the optimal timing of replacement of rental equipment owned by a large multi-location firm in the equipment rental industry	- SVM - LR - IBL	- Dynamic programming model	- Dataset includes information on 486 forest road construction projects, including data on project design, construction, and environmental factors for a period of over 20 years
Plisson, J., Mladenić, D., Ljubič, P., Lavrač, N., & Grobelnik, M. (2005) https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=10c5ec32e8e4b76f0428409aa738e03ca6ca3d24	Python	- Machine Learning - Identifying and structuring the expertise of employees within a company	- Clustering - Classification		- Data from Yahoo's employee database
Swink, M., Narasimhan, R., & Kim, S. W. (2005) https://doi.org/10.1111/j.1540-5414.2005.00079.x		- Study of the relationship between practices and performance - Trategy integration and enhanced manufacturing capabilities such as cost efficiency and flexibility serve as intermediaries by which practices affect performance			- Data from 57 North American manufacturing plants that are past winners and finalists in Industry Week's "American's Best" competition
Diefenbach, U., Wald, A., & Gleich, R. (2018) https://doi.org/10.1007/s00187-018-0261-5		- Cost management for organisational performance - Develop a model for a cost management control system (CMCS)			- Data of 251 European companies
Hjeltnes, T. A., & Hansson, B. (2005) http://www2.tisip.no/quis/public_files/wp7-cost-effectiveness-efficiency.pdf		- Comparison the cost-effectiveness and efficiancy of SMEs across industries and countries in seven European countries			- The data covered SMEs in manufacturing and service sectors in Austria, Finland, France, Germany, Italy, Spain, and the United Kingdom - The sample consisted of 7,234 SMEs, with sizes ranging from 10 to 249 employees.

Table 1. Cont.

Name/Reference	Environment	Summary and Specialty	Techniques		Dataset
			ML Methods	Theoretical Background	
Lombrano, A. (2009) https://doi.org/10.1016/j.resconrec.2009.04.017		- Machine Learning - Time Series Model - Comparison of four forecasting methods for the fluctuation demand for spare parts products at an Indonesian company			- Percentage of separate collection, collection and transport cost for normal waste, collection and transport cost for separated waste for the years of 2002, 2003, and 2004 for each Italian region
Ghanadiof, O. (2021) https://doi.org/10.24018/ejbmr.2021.6.3.903	SPSS	- Statistical method - Study of relationship between brand equity with an intention to buy agagin		- Descriptive statistics - Multiple regreesion - AMOS	- Data from survey to managers of the mining businesses and owners of machines
Aktepe, A., Yanık, E., & Ersöz, S. (2021) https://doi.org/10.1007/s10845-021-01737-8	Python	- Machine Learning - Demand forecasting - Forecast the number of spare parts of construction machinery requested in the future period by customer	- Linear regression - Multuple non-linear regression - Artificial neural networks - Support vector regression	-	- Data composed of the sales amount of 2010 to 2018 belonging to the manifold product group - Number of construction machine sold in the world - USD exchange rate and monthly impact rate
Ihnatovich, H. (2017) http://urn.kb.se/resolve?urn=urn%3Anbn%3Ase%3Akth%3Adiva-209044		- Machine Learning - Demand forecasting - Support construction equipment manufacturers, distributors, and suppliers in apprehending the equipment market	- ANN		- Economic indicators data for the time period 2005 quarter 1 (Q1) to 2016 quarter 4 is available through Oxford Economics database - Quarterly construction equipment sales data for the selected countries is gathered from Committee for European Construction Equipment (2017) and Hargrove & Associates, Inc (2017) databases
Kargul, A., Glaese, A., Kessler, S., & Günthner, W. A. (2017) http://www.ijscer.com/uploadfile/2017/0427/20170427032411542.pdf	Python	- Machine Learning - Prediction of heavy equipment demand	- SVM		- Sample data from over 111 construction projects between 2013 and 2015
Kusumastuti, R. D., & Bustaman, Y. (2022) https://doi.org/10.33555/embm.v9i2.197	Python	- Machine Learning - Time Series Model - Comparison of four forecasting methods for the fluctuation demand for spare parts products at an Indonesian company	- A-B-C Analysis - Moving Average - Simple Exponetial Smoothing (SES) - Exponential Smoothing (ES)		- Qualititive data included a description of the activities that compnay PT XYZ carries out in managing inventory - Quantatitive data in form of salesdata, inventory data, quantity data of the arrival of goods in the company PT XYZ
Mitchell Jr, Z. W. (1998) https://tc.idm.oclc.org/login?url=https://www.proquest.com/dissertations-theses/statistical-analysis-construction-equipment/docview/304463576/se-2	Python	- Machine Learning - Equipment management - Prediction of internal rental rates of machinery	- Linear regression model - Non-linear regression model	- Cumulative Cost Model	- Field data on 270 heavy construction machines from four different companies

Table 1. Cont.

Name/Reference	Environment	Summary and Specialty	Techniques		Dataset
			ML Methods	Theoretical Background	
Liu, C., AbouRizk, S., Morley, D., & Lei, Z. (2020) https://ascelibrary.org/doi/full/10.1061/%28ASCE%29CO.1943-7862.0001816?casa_token=afh2o_GC1dMAAAAA:uuXxUX8VO2szF17Yusq-GzB_CkXiCd4bZs205vb2WuAMkK5zJkD-ZGo97M29FONRWdtkjGYBHCaD	Python/Matlab	- Machine Learning - Accurately quantify the equipment lifecycle cost, incorporating both maintenance and ownership costs	- K-means clustering - Expectation-maximization (EM) algorithms		- A historical data set of ownership and maintenance costs for a mining truck model
Egonsson, E., Ly, T. T., & Bayarsaikhan, K. (2013) urn:nbn:se:lnu:diva-27427		- The importance of after-sales service in Swedish heavy equipment machinery industry - Customer relationship among three classified sizes of after-sales service providers			- Semi-structured interviews with three organization (one small, one medium and one large size after-sales service providers)

4. Conclusion

Industrial management can benefit from a comprehensive approach that incorporates macro risk factors, integrates AI technologies, and leverages insights from advanced scientific methods. By considering macro risk factors such as PESTLE (political, economic, social, technological, legal, and environmental) and ESG (environmental, social, and governance) in industrial management strategies, organizations can better navigate complex business environments, mitigate risks, and capitalize on emerging opportunities. AI technologies, including automation, data analysis, and predictive modeling, hold the potential to revolutionize industrial management by enhancing efficiency, reducing waste, and supporting informed decision-making. Recent advancements in AI, including OpenAI's language models and data analytics tools, offer valuable support for industrial management by analyzing complex datasets and providing actionable insights. These tools enable organizations to optimize decision-making, thereby achieving higher levels of productivity, sustainability, and resilience in industrial operations. OpenAI's contributions to AI innovation empower industrial managers to address both strategic and operational challenges more effectively.

In conclusion, integrating macro risk factors, AI technologies, and data-driven insights into industrial management promotes greater efficiency, reduces operational costs, enhances safety, and boosts productivity. As organizations adopt these advancements, industrial management is positioned for transformative growth, fostering operational excellence and sustainability across sectors.

Funding

This research received no external funding.

Author Contributions

Conceptualization, T.T.; writing—original draft preparation, T.T., S.J., J.L., Z.H., K.O.W. and Y.T. All of the authors read and agreed to the published the final manuscript.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement Statement

Not applicable.

Conflicts of Interest

The authors declare no conflict of interest.

References

1 Amiri M, Ardeshir A, Fazel Zarandi, MH, *et al*. Pattern Extraction for High-Risk Accidents in the Construction Industry: A Data-Mining Approach. *International Journal of Injury Control and Safety Promotion* 2016; **23**(**3**): 264–276.

2 Lee RG, Dale BG. Business Process Management: A Review and Evaluation. *Business Process Management Journal* 1998; **4**(**3**): 214–225.

3 Khan A. Project Scope Management. *Cost Engineering* 2006; **48**(**6**): 12–16.

4 Williams T. Identifying Success Factors in Construction Projects: A Case Study. *Project Management Journal* 2016; **47**(**1**): 97–112.

5 Al-Rubaiei QHS, Nifa FAA, Musa S. Project Scope Management through Multiple Perspectives: A Critical Review of Concepts. In AIP Conference Proceedings; AIP Publishing LLC: Melville, NY, USA, 2018; Volume 2016, p. 020025.

6 Drob C, Zichil V. Overview Regarding the Main Guidelines, Standards, and Methodologies Used in Project Management. *Journal of Engineering Studies and Research* 2013; **19**(**3**): 26.

7 Dumont PR, Gibson GE, Jr., Fish JR. Scope Management Using Project Definition Rating Index. *Journal of Management in Engineering* 1997; **13**(**5**): 54–60.

8 Fageha MK, Aibinu AA. Managing Project Scope Definition to Improve Stakeholders' Participation and Enhance Project Outcome. *Procedia-Social and Behavioral Sciences* 2013; **74**: 154–164.

9 Shirazi F, Kazemipoor H, Tavakkoli-Moghaddam R. Fuzzy Decision Analysis for Project Scope Change Management. *Decision Science Letters* 2017; **6**(**4**): 395–406.

10 Tian T, Deng J, Zheng B, *et al*. AI-Driven Transformation: Revolutionizing Production Management with Machine Learning and Data Visualization. *Journal of Computational Methods in Engineering Applications* 2024; 1–18.

11 Yazici HJ. The Role of Project Management Maturity and Organizational Culture in Perceived Performance. *Project Management Journal* 2009; **40**(**3**): 14–33.

12 Liang Y, Chen C, Tian T, *et al*. Fair Classification via Domain Adaptation: A Dual Adversarial Learning Approach. *Frontiers in Big Data* 2023; **5**: 129.

13 Obrutsky S. Comparison and Contrast of Project Management Methodologies PMBOK and SCRUM. 2015. Available online: https://www. coursehero. com/file/149980678/ResearchReportdocx/ (accessed on 1 November 2024).

14 Tian T, Chen X, Liu Z, *et al*. Enhancing Organizational Performance: Harnessing AI and NLP for User Feedback Analysis in Product Development. *Innovations in Applied Engineering and Technology* 2024; **3**(**1**): 1–15.

15 Odhiambo KO. Influence of Skills and Knowledge on the Relationship between Project Scope Management and Implementation of Economic Stimulus Projects in Public Secondary Schools in Kisumu County, Kenya. Ph.D. Thesis, University of Nairobi, Nairobi, Kenya, 2014.

16 Mahring M, Wennberg K, Demir R. Reaping Value from Digitalization in Swedish Manufacturing Firms: Untapped Opportunities. *Managing Digital Transformation* 2018; 41–63.

17 Li L. Investigating Risk Assessment In Post-Pandemic Household Cryptocurrency Investments: An Explainable Machine Learning Approach. *Journal of Asset Management* 2023; 1–13.

18 Man SS, Chan AH, Wong HM. Risk-Taking Behaviors of Hong Kong Construction Workers–A Thematic Study. *Safety Science* 2017; **98**: 25–36.

19 Cooper R, Edgett S, Kleinschmidt E. Portfolio Management for New Product Development: Results of an

Industry Practices Study. *R&D Management* 2001; **31**(**4**): 361–380.

20 Cooper DF, Grey S, Raymond G, *et al*. *Project Risk Management Guidelines*; Wiley: Hoboken, NJ, USA, 2005.

21 Torok R, Nordman C, Lin S. *Clearing the Clouds: Shining a Light on Successful Enterprise Risk Management*; Executive Report; IBM Global Business Services: Armonk, NY, USA, 2011.

22 Thamhain HJ. Leading Technology-Based Project Teams. *Engineering Management Journal* 2004; **16**(**2**): 35–43.

23 Samhain H. Managing Risks in Complex Projects. *Project Management Journal* 2013; **44**(**2**), 20–35.

24 Thamhain HJ. *Managing Technology-Based Projects: Tools, Techniques, People and Business Processes*; John Wiley & Sons: Hoboken, NJ, USA, 2014.

25 Thamhain HJ, Wilemon D. Building Effective Teams for Complex Project Environments. *Technology Management-New York* 1998; **4**(**3**): 203–212.

26 Altshuler AA, Luberoff DE. *Megaprojects: The Changing Politics of Urban Public Investment*; Brookings Institution Press: Washington, DC, USA, 2004.

27 Atkinson R, Crawford L, Ward S. Fundamental Uncertainties in Projects and the Scope of Project Management. *International Journal of Project Management* 2006; **24**(**8**): 687–698.

28 Harvett CM. A Study of Uncertainty and Risk Management Practice Related to Perceived Project Complexity. Ph.D. Thesis, Bond University, Robina, QLD, Australia, 2013.

29 Thamhain HJ. Leading Technology—Intensive Project Teams. In Proceedings of the PMI® Global Congress 2003—North America, Baltimore, MD, USA, 18 – 25 September 2003; Project Management Institute: Newtown Square, PA, USA, 2003.

30 Vidal LA, Marle F. Understanding Project Complexity: Implications on Project Management. *Kybernetes* 2008; **37**(**8**): 1094–1110.

31 Zhai L, Xin Y, Cheng C. Understanding the Value of Project Management from a Stakeholder's Perspective: A Case Study of Megaproject Management. *Project Management Journal* 2009; **40**(**1**): 99–109.

32 Boysen N, Fliedner M, Scholl A. A Classification of Assembly Line Balancing Problems. *European Journal of Operational Research*2 007; **183**(**2**): 674–693.

33 Münstermann B, Eckhardt A, Weitzel T. The Performance Impact of Business Process Standardization: An Empirical Evaluation of the Recruitment Process. *Business Process Management Journal* 2010; **16**(**1**), 29–56.

34 Xu H, Horn Nord J, Daryl Nord G, *et al.* Key Issues of Accounting Information Quality Management: Australian Case Studies. *Industrial Management & Data Systems* 2003; **103**(**7**): 461–470.

35 Thorpe B, Sumner P. *Quality Management in Construction*; Gower Publishing, Ltd: London, UK, 2004.

36 Klefsjö B, Wiklund H, Edgeman RL. Six Sigma Seen as a Methodology for Total Quality Management. *Measuring Business Excellence* 2001; **5**(**1**): 31–35.

37 Dent EB, Goldberg SG. Challenging "Resistance to Change". *The Journal of Applied Behavioral Science* 1999; **35**(**1**): 25–41.

38 Oreg S. Resistance to Change: Developing an Individual Differences Measure. *Journal of Applied Psychology* 2003; **88**(**4**): 680.

39 Vas A. Challenging Resistance to Change from the Top to the Shop Floor Level: An Exploratory Study. *International Journal of Strategic Change Management* 2009; **1**(**3**): 212–230.

40 De Reyck B, Grushka-Cockayne Y, Lockett M, *et al*. The Impact of Project Portfolio Management on Information Technology Projects. *International Journal of Project Management* 2005; **23**(**7**): 524–537.

41 Arias M, Saavedra R, Marques MR, *et al*. Human Resource Allocation in Business Process Management and Process Mining: A Systematic Mapping Study. *Management Decision* 2018; **56**(**2**): 376–405.

42 Gaonkar RS, Viswanadham N. An Analytical Framework for the Management of Risk in Supply Chains. *IEEE Transactions on Automation Science and Engineering* 2007; **4**(**2**): 265–273.

43 Cohen MA, Kunreuther H. Operations Risk Management: An overview of Paul Kleindorfer's Contributions. *Production and Operations Management* 2007; **16**(**5**): 525–541.

44 Kobrin SJ. Political Risk: A Review and Reconsideration. *Journal of International Business Studies* 1979; **10**: 67–80.

45 Braunstein E, Fortunato P, Kozul-Wright R. Trade and Investment in the Era of Hyperglobalization. *The Palgrave Handbook of Development Economics Critical Reflections on Globalisation and Development* 2019; 727–762.

46 Pitelis CN, Tomlinson PR. Industrial Organization, the Degree of Monopoly and Macroeconomic Performance—A Perspective on the Contribution of Keith Cowling (1936–2016). *International Journal of Industrial Organization* 2017; **55**: 182–189.

47 Örgün BO. Strategic Trade Policy Versus Free Trade. *Procedia-Social and Behavioral Sciences* 2012; **58**: 1283–1292.

48 Mulder HA, Rönnegård L, Fikse WF, *et al.* Estimation of Genetic Variance for Macro- and Micro-Environmental Sensitivity Using Double Hierarchical Generalized Linear Models. *Genetics Selection Evolution*2013; **45**(**1**): 1–14.

49 Quairel-Lanoizelée F. Are Competition and Corporate Social Responsibility Compatible?. *The Myth of Sustainable Competitive Advantage. Society and Business Review* 2011; **6**(**1**): 77–98.

50 Bowen A, Stern N. Environmental Policy and the Economic Downturn. *Oxford Review of Economic Policy* 2010; **26**(**2**): 137–163.

51 Kunst AE, Bos V, Lahelma E, *et al*. Trends in Socioeconomic Inequalities in Self-Assessed Health in 10 European Countries. *International Journal of Epidemiology* 2005; **34**(**2**): 295–305.

52 Arthur JB. The Link between Business Strategy and Industrial Relations Systems in American Steel Minimills. *Ilr Review* 1992; **45**(**3**): 488–506.

53 Younis H, Sundarakani B, Alsharairi M. Applications of Artificial Intelligence and Machine Learning within Supply Chains: Systematic Review and Future Research Directions. *Journal of Modelling in Management* 2022; **17**(**3**): 916–940.

54 Bergman J, Jantunen A, Viljainen S, *et al*. The Exploration of Future Service Innovations in the Radically Changing Business Environment within the Electricity Distribution Industry. *International Journal of Entrepreneurship and Innovation Management* 2008; **8**(**2**): 120–141.

55 Flyvbjerg B, Bruzelius N, Rothengatter W. *Megaprojects and Risk: An Anatomy of Ambition*; Cambridge University Press: Cambridge, UK, 2003.

56 Hübel B, Scholz H. Integrating Sustainability Risks in Asset Management: The Role of ESG Exposures and ESG Ratings. *Journal of Asset Management* 2020; **21**(**1**): 52–69.

57 Aich S, Thakur A, Nanda D, *et al*. Factors Affecting Egg towards the Impact on Investment: A Structural Approach. *Sustainability* 2021; **13**(**19**): 10868.

58 Mojtahedi SMH, Mousavi SM, Aminian A. Fuzzy Group Decision Making: A Case Using FTOPSIS in Mega Project Risk Identification and Analysis Concurrently. In Proceedings of the 2008 IEEE International Conference on Industrial Engineering and Engineering Management, Singapore, 8 – 11 December 2008; pp. 1769–1773.

59 Giese G, Lee LE, Melas D, *et al*. Foundations of ESG investing: How ESG Affects Equity Valuation, Risk, and Performance. *The Journal of Portfolio Management*2019; **45**(**5**): 69–83.

60 Cornell B. ESG Preferences, Risk, and Return. *European Financial Management* 2021; **27**(**1**): 12–19.

61 Cohen G. ESG Risks and Corporate Survival. *Environment Systems and Decision*s 2022; 1–6.

62 Hoang T. The Role of Integrated Reporting in Raising Awareness of Environmental, Social, and Corporate Governance (ESG) Performance. *Stakeholders, Governance and Responsibility* 2018; **14**: 47–69.

63 Gatzert N, Reichel P, Zitzmann A. Sustainability Risks & Opportunities in the Insurance Industry. *Zeitschrift für Die Gesamte VersicherUngswissenschaft* 2020; **109**: 311–331.

64 Karwowski M, Raulinajtys-Grzybek M. The Application of Corporate Social Responsibility (CSR) Actions for Mitigation of Environmental, Social, Corporate Governance (ESG) and Reputational Risk in Integrated Reports. *Corporate Social Responsibility and Environmental Management* 2021; **28**(**4**): 1270–1284.

65 Zumente I, Lāce N. ESG Rating—Necessity for the Investor or the Company?*Sustainability* 2021; **13**(**16**): 8940.

66 Cort T, Esty D. ESG Standards: Looming Challenges and Pathways Forward. *Organization & Environment* 2020; **33**(**4**): 491–510.

67 Psomas EL, Fotopoulos CV, Kafetzopoulos DP. Core Process Management Practices, Quality Tools, and Quality Improvement in ISO 9001-Certified Manufacturing Companies. *Business Process Management Journal* 2011; **17**(**3**): 437–460.

68 Tseng ML, Tan RR, Siriban-Manalang AB. Sustainable Consumption and Production for Asia: Sustainability through Green Design and Practice. *Journal of Cleaner Production* 2013; **40**: 1–5.

69 Metzger M, Polakow G. A Survey on Applications of Agent Technology in Industrial Process Control. *IEEE Transactions on Industrial Informatics* 2011; **7**(**4**): 570–581.

70 Tonchia S. *Industrial Project Management Planning, Design, and Construction*; Springer: Berlin, Germany, 2008.

71 Rezakhani P. Classifying Key Risk Factors in Construction Projects. *Buletinul Institutului Politehnic din lasi. Sectia Constructii, Arhitectura* 2012; **58**(**2**): 27.

72 Ahire SL, Dreyfus P. The Impact of Design Management and Process Management on Quality: An Empirical Investigation. *Journal of Operations Management* 2000; **18**(**5**): 549–575.

73 Chen L, Luo H. A BIM-Based Construction Quality Management Model and Its Applications. *Automation in Construction* 2014; **46**: 64–73.

74 *Cline, P. B*. Learning to Navigate Uncertainty. Available online: https://missioncti.com/wp-content/uploads/2020/05/Learning-To-Navigate-Uncertainty-v-2-4-May-2020-1.pdf (accessed on 1 November 2024).

75 Belousova M, Aleshko R, Zakieva R, *et al*. Development of Equipment Management System with Monitoring of Working Characteristics of Technological Processes. *Journal of Applied Engineering Science* 2021; **19**(**1**): 186–192.

76 Sun B, Jämsä-Jounela SL, Todorov Y, et al. Perspective for Equipment Automation in Process Industries. *IFAC-PapersOnLine*2017; **50**(**2**): 65–70.

77 Creyts JC, Carey VP. Use of Extended Exergy Analysis as A Tool For Assessment of the Environmental Impact of Industrial Processes. In *ASME International Mechanical Engineering Congress and Exposition*; American Society of Mechanical Engineers: New York, NY, USA, 1997; Volume 18459, pp. 129–137.

78 da Silva PRS, Amaral FG. An Integrated Methodology for Environmental Impacts and Costs Evaluation in Industrial Processes. *Journal of Cleaner Production* 2009; **17**(**15**): 1339–1350.

79 Croxton KL, Garcia-Dastugue SJ, Lambert DM, *et al*. The Supply Chain Management Processes. *The international Journal of Logistics Management* 2001; **12**(**2**): 13–36.

80 Lambert DM, García-Dastugue SJ, Croxton KL. An Evaluation of Process-Oriented Supply Chain Management Frameworks. *Journal of Business Logistics* 2005; **26**(**1**): 25–51.

81 Goel P, Datta A, Mannan MS. Application of big data analytics in process safety and risk management. In Proceedings of the 2017 IEEE International Conference on Big Data (Big Data), Boston, MA, USA, 11–14 December 2017; pp. 1143–1152.

82 Khan F, Rathnayaka S, Ahmed S. Methods and Models in Process Safety and Risk Management: Past, Present and Future. *Process Safety and Environmental Protection* 2015; **98**: 116–147.

83 Kourou K, Exarchos TP, Exarchos KP, *et al*. Machine Learning Applications in Cancer Prognosis and Prediction. *Computational and Structural Biotechnology Journal* 2015; **13**: 8–17.

84 Esteva A, Kuprel B, Novoa RA, *et al*. Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks. *Nature*2 017; **542**(**7639**): 115–118.

85 Tian T. Integrating Deep Learning and Innovative Feature Selection for Improved Short-Term Price Prediction in Futures Markets. *Ph.D. Thesis*, Illinois Institute of Technology, Chicago, IL, USA, 2024.

86 Van TN, Quoc TN. Research Trends on Machine Learning in Construction Management: A Scientometric Analysis. *Journal of Applied Science and Technology Trends* 2021; **2**(**03**): 96–104.

87 Hegde J, Rokseth B. Applications of machine learning methods for engineering risk assessment–A review. *Safety Science* 2020; **122**: 104492.

88 Thompson N, Squires W, Fearnhead N, *et al. Digitalization in Construction-Industrial Strategy Review, Supporting the Government' s Industrial Strategy*; University College London: London, UK, 2017.

89 Van Tam N, Quoc Toan N, Phong VV, *et al*. Impact of BIM-Related Factors Affecting Construction Project Performance. *International Journal of Building Pathology and Adaptation* 2021; **41**(**2**): 454–475.

90 Van Tam N, Huong NL, Ngoc NB. Factors Affecting Labor Productivity of Construction Worker on Construction Site: A Case of Hanoi. *Journal of Science and Technology in Civil Engineering (STCE)-HUCE* 2018; **12**(**5**): 127–138.

91 Van Tam N, Diep TN, Quoc Toan N, *et al*. Factors Affecting Adoption of Building Information Modeling in Construction Projects: A Case of Vietnam. *Cogent Business & Management* 2021; **8**(**1**): 1918848.

92 George MR, Nalluri MR, Anand KB. Application of Ensemble Machine Learning for Construction Safety Risk Assessment. *Journal of The Institution of Engineers (India): Series A* 2022; **103**(**4**): 989–1003.

93 Goh YM, Chua D. Neural Network Analysis of Construction Safety Management Systems: A Case Study in Singapore. *Construction Management and Economics*2013; **31**(**5**): 460–470.

94 Zhang H, Yang F, Li Y, *et al*. Predicting Profitability of Listed Construction Companies Based on Principal Component Analysis and Support Vector Machine—Evidence from China. *Automation in Construction* 2015; **53**: 22–28.

95 Nimdzi Insights. Artificial Intelligence: Localization Winners, Losers, Heroes, Spectators. 2019. *Available online:*https://www.nimdzi.com/category/localization/page/8/ (accessed on 1 November 2024).

96 Fischer L, Ehrlinger L, Geist V, *et al.* AI system engineering—Key challenges and lessons learned. *Machine Learning and Knowledge Extraction* 2020; **3**(**1**): 56–83.

97 Chapman P, Clinton J, Kerber R, *et al*. CRISP-DM 1.0: Step-by-Step Data Mining Guide; SPSS Inc.: Chicago, IL, USA, 2000; Volume 9, pp. 1–73.

98 Wirth R, Hipp J. CRISP-DM: Towards a Standard Process Model for Data Mining. In Proceedings of the 4th International Conference on the Practical Applications of Knowledge Discovery and Data Mining, Manchester, UK, 11–13 April 2000; Volume 1, pp. 29–39.

99 Shearer C. The CRISP-DM Model: The New Blueprint for Data Mining. *Journal of Data Warehousing* 2000; **5**(**4**): 13–22.

100 Kurgan LA, Musilek P. A survey of knowledge discovery and data mining process models. *The Knowledge Engineering Review* 2006; **21**(**1**): 1–24.

101 Mariscal G, Marban O, Fernandez C. A Survey of Data Mining and Knowledge Discovery Process Models and Methodologies. *The Knowledge Engineering Review* 2010; **25**(**2**): 137–166.

102 Kriegel HP, Borgwardt KM, Kröger P, *et al*. Future Trends in Data Mining. *Data Mining and Knowledge Discovery* 2007; **15**: 87–97.

103 de Abajo N, Diez AB, Lobato V, *et al*. ANN Quality Diagnostic Models for Packaging Manufacturing: An Industrial Data Mining Case Study. In Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Seattle, WA, USA, 22–25 August 2004; pp. 799–804.

104 Gersten W, Wirth R, Arndt D. Predictive Modeling in Automotive Direct Marketing: Tools, experiences and open issues. In Proceedings of the Sixth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Boston, MA, USA, 20–23 August 2000; pp. 398–406.

105 Hipp J, Lindner G. Analyzing Warranty Claims of Automobiles: An Application Description Following the CRISP-DM Data Mining Process. In Proceedings of the Internet Applications: 5th International Computer Science Conference, ICSC'99, Hong Kong, China, 13–15 December *1999*.

106 Guyon I, Elisseeff A. An Introduction to Variable and Feature Selection. *Journal of Machine Learning Research* 2003; **3**: 1157–1182.

107 Poh CQ, Ubeynarayana CU, Goh YM. Safety Leading Indicators for Construction Sites: A Machine Learning Approach. *Automation in Construction* 2018; **93**: 375.

108 Li L, Rong S, Wang R, *et al.* Recent Advances in Artificial Intelligence and Machine Learning for Nonlinear Relationship Analysis and Process Control in Drinking Water Treatment: A Review. *Chemical Engineering Journal* 2021; **405**: 126673.

109 Khayyam H, Javadi B, Jalili M, *et al*. Artificial intelligence and the Internet of Things for Autonomous Vehicles. *Nonlinear Approaches in Engineering Applications: Automotive Applications of Engineering Problems* 2020; 39–68.

110 Wamba-Taguimdje SL, Fosso Wamba S, Kala Kamdjoug JR, *et al*. Influence of Artificial Intelligence (AI)

on Firm Performance: The Business Value of AI-Based Transformation Projects. *Business Process Management Journal* 2020; **26**(**7**): 1893–1924.

111 Hassani H, Silva ES. The Role of ChatGPT in Data Science: How AI-Assisted Conversational Interfaces Are Revolutionizing the Field. *Big data and Cognitive Computing* 2023; **7**(**2**): 62.

112 Wang FY, Yang J, Wang X, *et al*. Chat with Chatbot on Industry 5.0: Learning and Decision-Making for Intelligent Industries. *IEEE/CAA Journal of Automatica Sinica* 2023; **10**(**4**): 831–834.

113 Lei X, Tang Q, Zheng Y, *et al*. High-Entropy Single-Atom Activated Carbon Catalysts for Sustainable Oxygen Electrocatalysis. *Nature Sustainability* 2023; 1–11.