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Application Of Computational Methods For Risk Assessment And Industrial Management

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Computational techniques are now crucial for evaluating business risks and managing industrial works. Nowadays, business sectors utilize a range of computational methods to improve management systems by making well-informed decisions. Numerous methods, including cloud computing, machine learning, predictive maintenance, and the respective, have been found to be helpful in starting a business process that is efficient in recognizing and evaluating hazards within the company. A secondary systematic review has been conducted in this study with thematic analysis that has focused on such critical components. Furthermore, the market expansion for these computational techniques has projected that their utilization is growing steadily and will continue to do so in the future. Thus, it is also possible to state that their efficacy in risk assessment and company management is justified.

Keywords: Computational methods, Risk assessment, Industrial management, Quantitative risk assessment, Simulation, Predictive maintenance.

Introduction

The concept of computational method can be described as a technique of using computers to solve scientific, mathematical, engineering, or other problems (Kandasamy et al. 2020). Computational methods are used to design large-scale engineering systems by implementing faster and more reliable methods. Global companies are currently using computational methods such as risk assessment, which might include machine learning, quantitative risk assessment, or simulation. On the other hand, these methods are also used in industrial management through system analysis, evaluation, and optimization along with scientific computing and numerical analysis (Ganin et al. 2020). As a result, computational methods have become important in global business platforms that address business uncertainties with the aid of computing resources.

Background and Rationale

The application of computational methods involves the identification, evaluation, and monitoring of potential risks in business enterprises. According to Frank et al. (2020), business compliance efforts can be recognized by using techniques of computation so that internal controls can be implemented and monitored effectively. Examples of applications can be seen through the Monte Carlo simulations that help in probability analysis and decision trees for the classification of risks (Hegde & Rokseth, 2020). Besides, industrial management can be done by implementing Predictive maintenance by using Machine Learning or quality control by utilizing statistical process control (SPC). Several computational tools are also available such as MATLAB, Python Libraries, R programming, Simulink, and cloud-based platforms. On the other hand, Kandasamy et al. (2020) have argued by saying that real-time monitoring can be used through sensors and IoT devices. Predictive maintenance can be done by using Data Analytics which results in improved accuracy in assessing risks and enhanced decision-making.

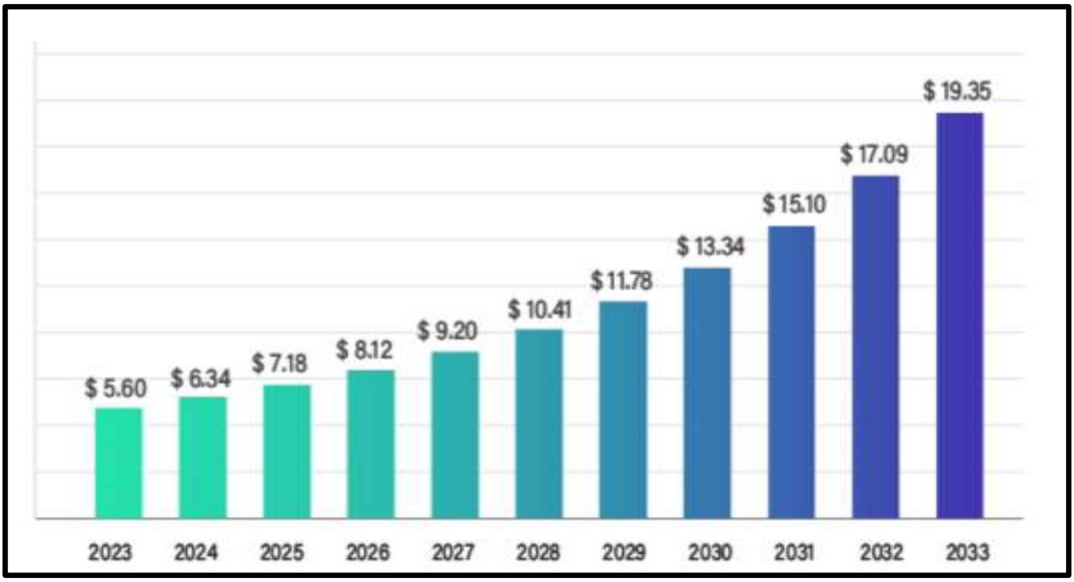

Figure 1: Computational biology market

(Source: Towards Healthcare, 2024)

Figure 1 explains the global computational biology market which was estimated to be $5.60 billion in 2023 (Towards Healthcare, 2024). It is further expected to grow by $19.35 billion in 2033. The annual growth rate (CAGR) of this sector is 13.20% between the period of 2024-2033. The rapid development in this market is visible due to advancements in genomics and bioinformatics. However, Frank et al. (2020) have shown that using computational methods comes with the issues of cost, accuracy, errors, interpretation, computational time, and user expertise. It is a powerful tool that requires significant expertise to solve scientific issues and engineering problems. The application of this technique is also limited in the complexities of the problems and the efficiency of the algorithms (Ganin et al. 2020). Thus, the availability of computing resources remains a significant problem in using these methods in industrial management.

Research aim and objectives

Aim

The research aims to critically analyze the application of computational methods in assessing risks and managing various global business industries.

Objectives

RO1: To determine the techniques used by computational methods in risk assessment and industrial management

RO2: To evaluate benefits obtained from computational methods to assess risks and manage business industries

RO3: To mention the challenges while implementing computational methods in risk assessment and industrial management

Literature Review

Computational methods or techniques used to ensure risk assessment and industrial management

Various techniques are available that can be utilized for risk assessment as well as industrial management. As per the view of Banerjee Chattapadhyay et al. (2021), probabilistic analysis can be done in a complex system by using Monte Carlo simulations. Event-tree analysis (ETA) can be used as an accident scenario modelling along with Hazard and Operability (HAZOP) Studies as a process of hazard identification. Moreover, the usage of Neural Networks is widespread as a predictive modelling used for pattern recognition of data and information. However, as argued by Zografopoulos et al. (2021), Genetic Algorithms are useful in optimizing and minimizing risks. As a result, an efficient risk assessment can be ensured by using such computational methods and techniques in a business atmosphere.

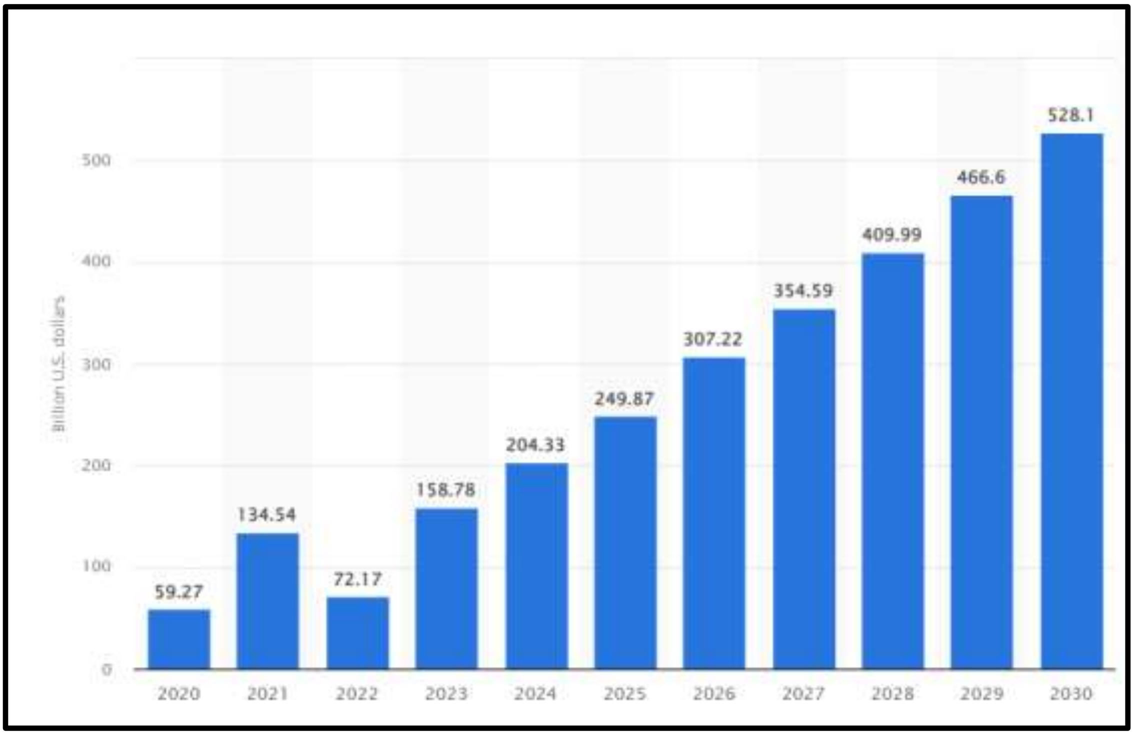

Figure 2: Global Machine Learning Market Size 2020-2030

(Source: Statista, 2024)

Figure 2 presents the market size of the global Machine Learning from 2020 to 2030. It has shown that the market has grown worldwide by $158.78 billion in 2023 which is expected to grow by $528.1 billion by 2030 (Statista, 2024). AI computing is considered to be a math-intensive process that calculates Machine Learning (ML) algorithms. Additionally, ML can be typically used to accelerate the systems and software that are being worked on for risk assessment or management. Hence, industrial management is widely done by using Predictive Maintenance, Quality Control, Supply Chain Optimization, Total Productive Maintenance (TPM), and the respective (Banerjee Chattapadhyay et al. 2021).

Benefits of using computational methods for risk assessment and industrial management

Global business firms are obtaining significant benefits by using computational methods as they improve accuracy in identifying quantitative risk assessments. It helps in providing data-driven insights to companies that enable them to make informed decisions (Lin et al. 2020). Moreover, the benefit of automated risk assessment reduces the manual effort of identifying risks which increases the efficiency of business firms. Companies can also reduce uncertainties by using Probabilistic modelling that results in quantifying uncertainties. In this way, global companies can also avoid regulatory issues by meeting regulatory requirements.

Figure 3: Benefits of cloud computing in the manufacturing process

(Source: Influenced by Hegde & Rokseth, 2020)

Cloud computing is an integral part of computational methods which is beneficial for global business firms. As mentioned by Hegde & Rokseth (2020), cloud computing in the manufacturing process helps in improving scalability, cost optimization, security, data storage and processing, and predictive maintenance. This method is used in various business industries which have a market growth of $446.51 billion in 2022 and it is also expected to reach $1 trillion in 2028 (Mordor Intelligence, 2024). It benefits companies by increasing production efficiency, reducing errors, and increasing ROI.

Identification of challenges in using computational methods in risk assessment and industrial management

Despite the benefits obtained from computational methods, they come with data-related challenges and methodological challenges the most. As suggested by Jarada et al. (2020), computational methods are complex and can damage data quality, accuracy, data integration, model selection, and interpretability of results. For instance, small biopharma companies often face challenges in implementing automation that scientists find difficult to work with complex and larger datasets. Besides, Big Data is a customizable power and is used as an advanced analytical tool that can be removed as it slows down innovation (Agamah et al. 2020). Consequently, shareability, reproducibility, and traceability of computational analysis are affected by more challenges in business firms. Business industries often face challenges in managing teams and projects with computational methods and approaches (Zografopoulos et al. 2021). As a result, they need to split up tasks that require additional time and effort to design scientific processes.

Method

The study has followed a secondary qualitative method by including peer-reviewed journals and articles. This method is beneficial as it provides access to a larger amount of data that is difficult to collect on its own (Ahmetoglu et al. 2022). Credible sources have been accessed as the selection of the databases is important to increase the efficiency of the current study. A few effective keywords such as “computational methods”, “risk assessment”, “industrial management”, and “scientific computing”, and the respective are used to obtain only relevant information. Hence, it has provided an opportunity to develop qualitative theories by using raw data from the existing published studies.

A systematic review method has been followed in this study that has acknowledged the usage of the Boolean search strategy and PRISMA as a screening process. It has also benefited the study by improving its transparency by explicitly using this method. As commented by Brous et al. (2020), systematic reviews assist in reducing biases that are influenced by accessible research. It concerns methodological gaps and designs of previous studies so that further positive contributions can be made in the respective research background. A thematic analysis has been done by forming themes to meet the research objectives. As a result, using this method has been proven to be advantageous to improve the outcomes of the study.

Results

Boolean search strategy

Keywords	**AND/OR**	**Keywords**	**AND/OR**	**Keywords**	**Search results**
Computational methods	**AND**	**Risk assessment**	**AND**	**Industrial management**	**ResearchGate= 1045**

Scientific computing	**AND**	**Cost optimization**	**OR**	**Cloud computing**	**ProQuest=989**
Automated risk identification	**OR**	**Predictive maintenance**	**AND**	**Production efficiency**	**ScienceDirect=212**

Table 1: Boolean search results

(Source: Influenced by Jarada et al. 2020)

Table 1 presents the Boolean search results mentioning the keywords that have assisted in finding only relevant journals and articles for this study. Individual search results from the accessed databases have also been mentioned in this table.

PRISMA

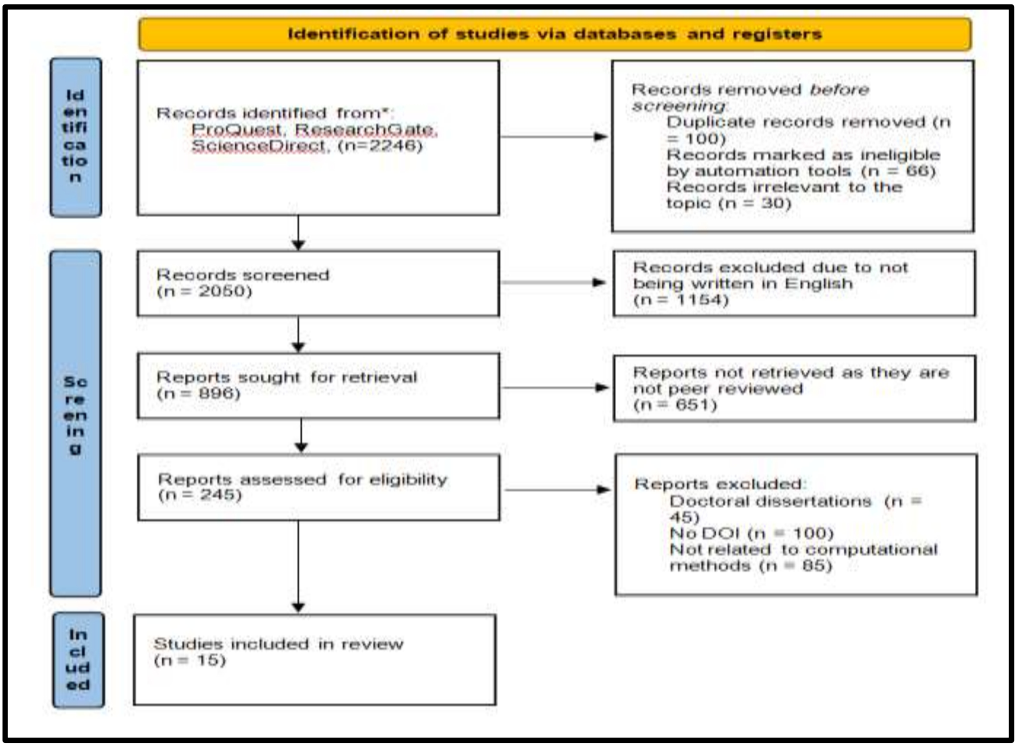

Figure 4: PRISMA

(Source: Influenced by Zografopoulos et al. 2021)

Figure 4 is the presentation of the PRISMA diagram that has worked as a screening tool in this qualitative study. It has been mentioned that a total of 15 peer-reviewed articles and journals have been selected for the data analysis process. Other obtained results have been excluded as they lacked relevance, DOI, language, and other ineligibility.

Axial coding

Authors	**Codes**	**Themes**
Mitici et al. (2023) Tichý et al. (2021) Nunes et al. (2023) Lee & Mitici (2023) Keleko et al. (2022)	Risk assessment, predictive maintenance, probabilistic analysis, hazard identification	"Theme 1: Probabilistic analysis and Predictive maintenance are the best-suited techniques for assessing risks and industrial management respectively"
Abdar et al. (2021) Faes et al. (2021) Abbaszadeh Shahri et al. (2022) Rising et al. (2022) Caldeira & Nord (2020)	Risk quantification, uncertainty reduction, computational techniques, risk aversion	"Theme 2: Quantifying risks and reducing uncertainties are the major benefits of using computational methods"
Whang et al. 2023 Aldoseri et al. 2023	Data quality, data interpretation accuracy, and data analysis challenges	"Theme 3: Data quality and accuracy are the main challenges

Wu et al. (2021) Shrestha et al. (2021) Antons et al. (2023)		that organizations face while using computational methods”

Table 2: Axial coding

Table 2 presents the axial coding that clearly mentions the formed themes directly addressing the research objectives. Initial codes and respective authors for their selected journals and publications have also been mentioned in this coding table.

Analysis

Theme 1: Probabilistic analysis and Predictive maintenance are the best-suited techniques for assessing risks and industrial management respectively

Probabilistic analysis is considered to be significant for risk assessment as it helps in quantifying uncertainties. Numerical representation of risks can be done by following this technique which is also flexible and can be applied to various risks such as operational or financial (Mitici et al. 2023). Moreover, it is an informative technique among most of the computational techniques that shows the probability of the risk outcomes. It supports informed decision-making that is effective in avoiding risks with effective measures after their potential identification. However, as argued by Tichý et al. (2021), its real-world application might be done in the aerospace, energy sector, manufacturing industries, and transportation for the best outcome. As a result, model validation, verification, continuous monitoring, and collaboration among experts can be achieved (Nunes et al. 2023).

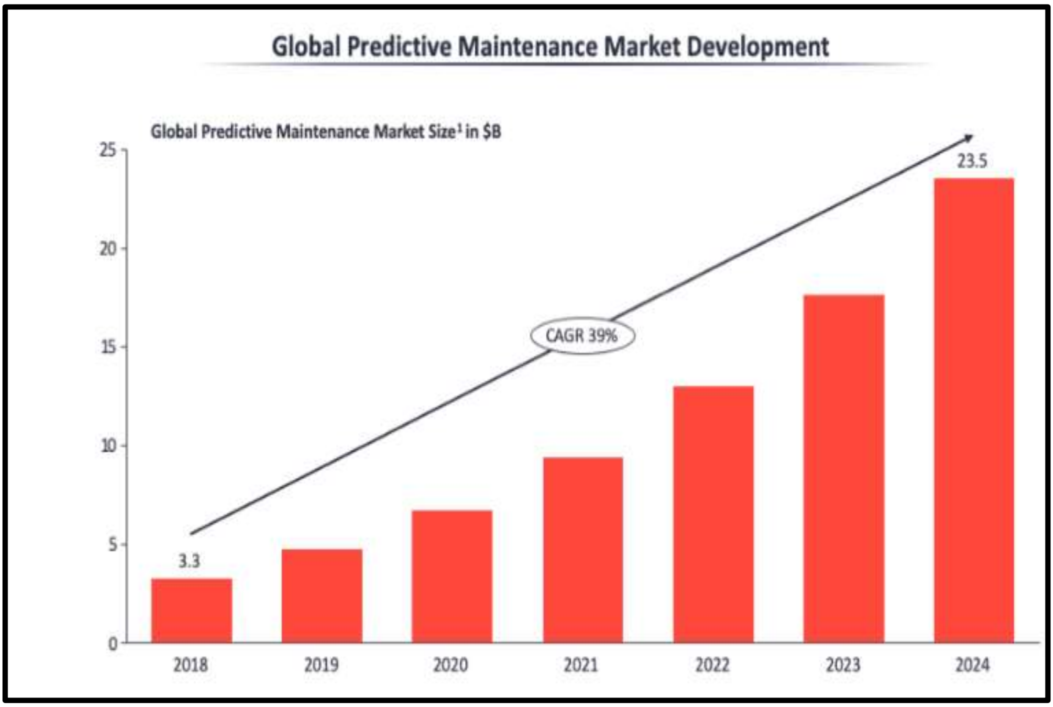

Figure 5: Global market of Predictive Maintenance

(Source: IoT Analytics, 2019)

Figure 5 showcases a prediction of the global market development of Predictive maintenance from 2018 to 2024. It has projected that the market value was $3.3 billion in 2018 which is expected to grow with a CAGR rate of 39% (IoT Analytics, 2019). Besides, it helps in industrial management by reducing downtime by minimizing unexpected failures. The maintenance schedule in different business industries can be maintained for an optimal time with the right implementation of this technique. On the contrary, as contrasted by Lee & Mitici (2023), the usage of ML algorithms, sensor-based monitoring, and vibration analysis can be useful for industrial management. Thus, downtime of business production is reduced with maintenance optimization by utilizing these computational methods (Keleko et al. 2022).

Theme 2: Quantifying risks and reducing uncertainties are the major benefits of using computational methods

Computational methods are beneficial for global business firms as quantified risks are crucial for stakeholders to initiate informed decisions. As determined by Abdar et al. (2021), quantified risks help in prioritizing risks to decide the risk mitigation efforts. Companies can focus on resource allocation more effectively by identifying potential risks so that they can be avoided with efficiency. Additionally, regulatory compliance can be demonstrated with this method which adds advantages for global business firms. Contrarily, Faes et al. (2021) have contrasted by arguing that computational methods must be chosen carefully to reduce uncertainties and quantify risks. As a result, the implementation of the Bayesian networks and probabilistic fault trees can be used.

On another note, risk quantification can be done that benefits stakeholder communication to improve business outcomes. In this context, Abbaszadeh Shahri et al. (2022) have shown that uncertainty avoidance in a business boosts the confidence and morale of employees as well as stakeholders. It also helps in increasing accuracy in risk avoidance which results in better productivity and organizational outcome. It leads to enhanced reliability in various industrial operations by reducing or avoiding uncertainties. On the other hand, as opposed to Rising et al. (2022), reduced uncertainties enable global businesses to minimize unnecessary expenditures. Therefore, computational methods are beneficial through their real-world applications in supply chain management, cybersecurity, industrial process control, and the respective (Caldeira & Nord, 2020).

Theme 3: Data quality and accuracy are the main challenges that organizations face while using computational methods

Data quality challenges are prominent in utilizing computational methods that consist of inaccurate or incomplete data, inconsistent data, and missing data. Data accuracy challenges include measurement errors, sampling biases, data entry errors, and model assumptions (Wu et al. 2021). In this context, it can be determined that poor data quality results in inaccurate predictions of risks that heavily impact the decision-making processes of business firms. In addition, it leads to reduced model reliability which increases uncertainties in industrial management. The result of such inconvenient data analysis decreases confidence in results along with an overall poor business outcome. However, Aldoseri et al. (2023) have argued by saying that technologies such as data profiling, cleansing tools, and ML algorithms can help in improving data quality. As a result, Data Quality Scanner and DataLadder are used as tools to ensure the accuracy of data.

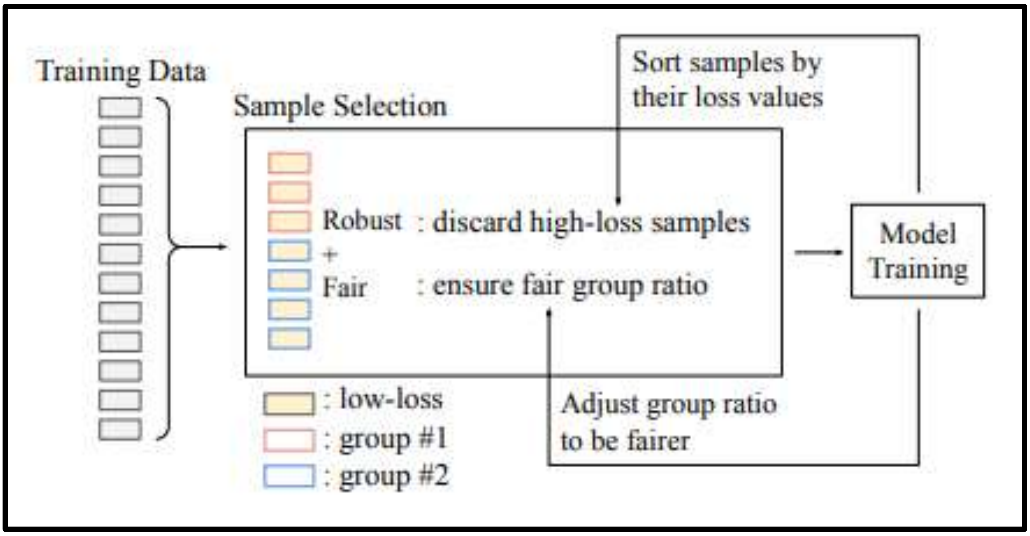

Figure 6: Adaptive sample selection

(Source: Influenced by Whang et al. 2023)

Figure 6 projects the diagram of an adaptive sample selection that is useful in a computational method. It has shown that it is a complex system that includes training data, sample selection, sorting samples, adjusting data groups, and model training (Whang et al. 2023). It can be challenging for companies to use such complex data analysis processes due to a lack of employee skill set and expertise. For instance, global financial institutions often face challenges in utilizing data quality tools to enhance risk assessment. It also becomes challenging for retail companies to use data cleansing tools to obtain customer insights (Shrestha et al. 2021; Antons et al. 2023). Therefore, companies mostly use data quality metrics for predictive maintenance as it is reliable and common in usage.

Discussion

The critical analysis of the research has focused on exploring the impact of computational methods in identifying risks and managing business industries. As discussed by Ganin et al. (2020), the identification of the best-suited computational techniques plays an important role in its outcome. In this case, the study has projected that Probabilistic analysis is advantageous in minimizing risks. Industrial management can be further benefited by using the technique of Predictive maintenance. It helps in meeting the first objective of the study by critically discussing the computing techniques. In contrast, Kandasamy et al. (2020) have expressed their concern that using such techniques benefits global companies by ensuring risk quantification and reduction of uncertainties. As a result, it meets the second objective by demonstrating the benefits obtained by computational methods in both of the cases.

On the other hand, business firms are recently facing immense challenges in assuring data quality and accuracy in identifying business risks. Organizational teams find it difficult to work with complex and huge datasets which degrades the quality of data interpretation (Banerjee Chattapadhyay et al. 2021). Besides, skill sets are different which is essential to be improved in order to improve the data quality which turns out to be also challenging in this context. Therefore, such critical evaluation of the challenges helped in meeting the third and final objective of this study.

Conclusion

From the above critical analysis, it can be concluded that computational methods have become important in assessing business risks. Business industries are currently using various computational techniques to make informed decisions to enhance management systems. Several techniques have been identified such as cloud computing, ML, predictive maintenance, and the respective that help in initiating such an effective business process for identifying and assessing risks in the business. Moreover, the market growth of these computational methods has also shown that their usage is constantly increasing and will rapidly increase in the future. Hence, their effectiveness in assessing risks and effective management of business management can also be proved.

Limitations and future scope

The selected studies for this study lack statistical information regarding various computational methods that are globally used in business platforms. Such information can provide in-depth insights into their market and current usage on businesses (Lin et al. 2020). Besides, these studies are also limited in providing theoretical knowledge on technological advancement that has taken place with the usage of computational methods. Previous studies also lacked interpreting data on the association of computational methods and their appropriateness in assessing organizational risks along with industrial management. As a result, these gaps or limitations have been addressed in the present study increasing its significance.

The study has the future scope of exploring on deeper levels in terms of the association of computational methods and organizational management. The study lacks focus on the techniques that can be applied in mitigating the challenges while implementing these methods. Organizations might face issues in methodological aspects of their implementation which must be explored at deeper levels in future studies (Frank et al. 2020). The selection of utilizing such methods is found to be crucial which can be covered in future studies for a better outcome.

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