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Research Paper

Business Process Management Capabilities for Sustainable Life Cycle Assessment and Reliability-Centered Maintenance Decision-Making Implementations

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Abstract

Life Cycle Assessment (LCA) and Reliability-Centered Maintenance (RCM) are complementary. Several studies have attempted to integrate both approaches for a more comprehensive assessment of business impacts and to make more sustainable decisions. This article provides a valuable cross-disciplinary contribution by bridging LCA and RCM in the mining sector to explore how the integration of LCA and RCM, based on business process management, affects the sustainability of decision-making. The methodological approaches include bibliometric analysis, Failure Mode and Impact Analysis (FMECA), and simulation. The results show that LCA and RCM are complementary and can be modeled in a holistic way (system theory) based on business process management. Bibliometric analysis confirms the need for more research into digital tools for data integration. Document analysis provides information on how the case study mining industry is performing against global maintenance practices to make more sustainable decisions. The FMECA complements the evaluations provided in this article with qualitative information on the process of operationalization of the proposed integrated framework. FMECA provides data on possible failure modes, their effects, and the criticality of each component. Based on the scenario impact assessment using the key parameters of the LCA and RCM measurements, the simulation results show that the combined business processes of the LCA and RCM can be captured and tested, aimed at quantifying these business processes for the mining sector used as a case study.

Keywords: *Bibliometric Analysis, Business Process, Decision-Making, Life Cycle Assessment, Reliability-Centered Maintenance*

INTRODUCTION

A sustainable business operates in a way that minimizes its negative impact on the environment while also ensuring long-term viability and profitability. It focuses on balancing the needs of the present with those of future generations, integrating environmental considerations into its core business strategies (Boson et al., 2023). Life Cycle Assessment (LCA) is primarily known for its focus on environmental impacts. LCA is a tool for assessing the potential environmental impact of a product throughout its life cycle. The term product covers goods, technology, and services (Theilig et al., 2024). Integrating LCA and digital tools supports sustainability and decision-making initiatives (Cerchione et al., 2025). A review of publications calls for more research to assess the impact of LCA businesses and to allow for more sustainable decisions. To go over a few pieces of LCA literature that demonstrate how crucial the decision-making model is to LCA implementations. The literature (Subal et al., 2024) looks into how applicable LCA techniques are to business and government decision-making. The study employed a semi-quantitative questionnaire and qualitative interviews to gather data on the relevance of LCA in decision-making. The questionnaire was structured into three parts: impacts of LCA on past decisions, importance of LCA in decision-making, and general specifications. Qualitative interviews

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were conducted with six participants to gain in-depth insights into LCA's application in large companies and public authorities. The outcomes indicate 45% of surveyed organizations integrate LCA in most decisions; 29% do not integrate it at all. The results affirm LCA is primarily used for product development and strategic decisions. Additionally, public authorities consider environmental aspects in regulations, but LCA results are not the sole influence. Notable key barriers in the investigation include prioritization of non-environmental factors, complexity of LCA methods, and data availability. Suggesting future research directions, the authors propose that investigations should focus on specific sectors or regions for deeper insights. In the article (Theilig et al., 2024), LCA is utilized to evaluate the environmental impacts of building parts throughout their entire life cycle, including production, use, and end-of-life phases. It identifies quantifiable criteria such as greenhouse gas emissions, energy demand, and circularity of materials, which are essential for sustainable building design. By integrating LCA with multi-criteria decision-making (MCDM), decision-makers can systematically assess and select the best design alternatives based on multiple environmental criteria. The methodology employs the Analytic Hierarchy Process (AHP) and Analytic Network Process (ANP) as the primary multi-criteria decision-making (MCDM) methods. A structured approach is followed, including defining the problem, selecting lifecycle-based criteria, evaluating alternatives through pairwise comparisons, and ranking them based on weighted criteria. The methodology integrates LCA to ensure environmental considerations are factored into the decision-making process for sustainable building design. A total of 29 relevant criteria are identified and categorized into four main areas: emissions, energy, resources, and circular economy. Sensitivity analysis indicated that the correlation between criteria significantly influenced the final rankings, highlighting the importance of considering interdependencies in the decision-making process. The authors for future research directions propose an emphasis on the development of limit values and regulations at the building part level to guide planners in achieving sustainable building designs. Additionally, the article encourages further integration of life cycle-based approaches and MCDM methods in early-phase decision-making to enhance the environmental performance of buildings and support the transition to a circular economy.

Lots of research reports on the use of Reliability Centered Maintenance (RCM) to enhance equipment performance, and specifically the reduction of plant downtime (Eriksen et al., 2021). However, despite investments in RCM policies, some restrictions still exist. These include insufficient data extraction, ineffective analysis of completed paper-based maintenance work orders, and ineffective performance of the Failure Mode and Effects Criticality Analysis (FMECA). One way to mitigate some of these problems is to use digital technology in the implementation of the RCM (Satapathy & Chauhan, 2024). Digital tools can greatly improve data for data-driven maintenance decisions (De Sordi, 2023). In other words, RCM is a methodology that maximizes the reliability of assets through the use of digital tools. A review of publications calls for more research that assesses the impact of the use of RCM applications in business and enables more sustainable choices to be made. To summarize, a few RCM literature that demonstrate how crucial the decision-making model is to RCM implementations. In the literature (Ma et al., 2020), the document discusses a data-driven approach to predictive maintenance in RCM. It emphasizes the integration of expert decision-making with quantitative analysis for optimal maintenance strategies. A Monte-Carlo simulation is proposed for maintenance strategy selection based on failure characteristics. The approach incorporates Building Information Modelling (BIM) and Geographic Information Systems (GIS) for data structuring. A prototype system was developed to streamline maintenance decision-making in business parks, reducing labour costs and enhancing objectivity. The outcomes suggest improving data acquisition methods for maintenance decision-making, particularly for hard-to-obtain data like maintenance material costs. It proposes the creation of a cloud database to share maintenance data across different business parks, enhancing user-friendliness and data accessibility. Suggested future work suggests integrating IoT sensors for real-time data collection and more accurate maintenance decision-making. The body of work (More et al., 2024) discusses the importance of hybrid maintenance models in decision-making for asset management, emphasizing the balance between cost and predictive maintenance strategies. It highlights the advantages of using methodologies like the FREEDOM algorithm for assessing domino effects in chemical processes. Additionally, it summarizes various decision-making tools, outlining their advantages and disadvantages. The authors for future research propose integrating cost, risk, and performance in maintenance decision-making to reduce uncertainties and deliver robust solutions. The author suggests that emphasis should be placed on developing economic models that account for non-economic overheads and the interdependence of equipment. Additionally, exploring the quantification of risk and enhancing the integration of quantitative methods with existing economic models is recommended.

LCA and RCM approaches are complementary. In the automobile industry, LCA can evaluate environmental impacts across vehicle life cycles, focusing on resource use, emissions, and pollution. Environmental impacts of vehicle maintenance and repairs are minimal in short-term replacement cycles. Optimization models suggest that replacing older cars can reduce environmental burdens, balancing new car benefits against production costs. Aging vehicle fleets, particularly in less affluent regions, pose challenges due to increased operational costs and lower fuel efficiency. The authors of the literature (Danilecki et al., 2023) employed LCA to evaluate the environmental impacts of Ford Focus passenger cars across various life cycle stages, utilizing data from Ecoinvent for modelling. The vehicle replacement optimization model is based on cumulative life cycle impacts, assessing maintenance scenarios and technological improvements to minimize environmental burdens. Simulations are conducted using a solver compatible with spreadsheets, incorporating detailed service data and operational parameters to inform decision-making on vehicle replacement. The authors suggest that future research should focus on improving inventory data to align with advancements in vehicle technology, particularly for optimizing Internal Combustion Engine Vehicle (ICEV) replacement policies with Electric Vehicles (EVs). There is also a need to assess the life cycle impacts of EV components, such as batteries, and their maintenance and end-of-life effects. In the aerospace, defense, and renewable energy industries, a case study in the literature (Gaikwad, 2025) focused on the challenges faced by electronic systems in harsh environments (high temperatures, mechanical stress, humidity). The authors utilized advanced simulations (FEA, CFD), real-time monitoring, and digital twin technology for reliability estimation. The results present an enhanced predictive maintenance framework capable in reducing downtime while the LCA outcomes highlight sustainability issues and the need for more research that develops integrated frameworks combining advanced testing, machine learning, and sustainability metrics to improve reliability and environmental impact of electronics. In the infrastructure sector, LCA can evaluate the environmental impacts of concrete structures throughout their entire life cycle, from material extraction to demolition. In the literature (Wang et al., 2022), LCA and RCM are integrated to analyze the carbon emissions and costs associated with different maintenance strategies for RC beams. The outputs aim to optimize maintenance schedules that balance reliability, cost, and environmental impact, ultimately prolonging the service life of the structures. The authors for future studies recommend the use of digital technologies for predictive maintenance and real-time monitoring of bridge conditions to enhance decision-making. Additionally, expand LCA frameworks to include social and economic factors, providing a more comprehensive assessment of sustainability in infrastructure projects.

Ultimately, the key aim of the authors is to highlight the need for more research on the use of data-integration tools, a quantitative and qualitative method for evaluating and improving decision-making. However, no documents from current publications reviewed follow a Business Process Management (BPM) perspective for developments, which necessitates a gap and a core objective in this article. The gap involves comparing and highlighting the advantages of the BPM approach for developing decision-making frameworks to other existing methods that combine LCA and RCM. Cost considerations and data integration facilitate linkages between LCA and RCM (Backes & Traverso, 2023; Barbero et al., 2024; Hannouf et al., 2024; Hussin et al., 2023; Mandade et al., 2023; Sifonte & Reyes-Picknell, 2017; Tao et al., 2023). While LCA focuses on the total cost of ownership, including the cost of environmental protection, RCM considers the cost of servicing potential faults. As regards data integration, both LCA and RCM require the collection and analysis of data for informed decision-making. This article focuses on the data integration of LCA and RCM protocols through business processes for a more comprehensive assessment of business impacts and to make more sustainable decisions. This article provides a valuable cross-disciplinary contribution by bridging LCA and RCM in the mining sector to explore how the integration of LCA and RCM, based on business process management, affects the sustainability of decision-making.

Based on the research gap defined above, the following questions on the relationship between BPM, LCA, and RCM arising from the abovementioned developments and theoretical gaps arise.

RQ1: Are there any recent findings or contributions in this field that point to a correlation between RCM and the LCA implementations?
RQ2: How do mining industries measure up against global maintenance practices to make more sustainable decisions?
RQ3: Does BPM affect the capacity of the proposed integrated implementation of LCA and RCM to make sustainable decisions, and are there possible links between the business processes of LCA and RCM?
RQ4: Are digital tools effective for data integration and efficient for the proposed LCA and RCM integration framework?
RQ5: What are the pilot impact assessments of the proposed LCA and RCM integration framework?
RQ6: Can the proposed LCA and RCM integration framework be replicated and applied to support real-world decision-making and its relevance to sustainability?

LITERATURE REVIEW

Systems theory regards an enterprise as a holistic, complex, and interdependent system in which each business process (or subsystem) affects and is affected by other business processes (or subsystems). Systemic theory stresses the importance of understanding the interrelationships between these business processes (or subsystems) to enable efficient interdependence, management, and decision-making (Watson & Romic, 2025). The systems theory determines which management approach is better suited for cooperation in working together to achieve a common purpose or aim. Several writers make use of systems theory and the concept of cybernetic systems interchangeably. In most cases, the terminology refers to cybernetics as a proper subset of the general systems category, which includes feedback loops. The main characteristics of the holistic view, open systems, feedback loops, synergies, adaptability, stability, hierarchy, interdependence, and resilience are summarised in the theory of systems. To learn more about systems theory, check out the authors (Mullins et al., 2020; Neske et al., 2024; Suter et al., 2013). The authors provide proof of systems theory applications and examples in the business world. These include applications in marketing, sales, supply chain, operations, human resources, and organizational transformations. The authors list the following advantages of using systems theory based on the applications.

(i) Better problem-solving: Provides a framework for comprehending how a business entity is interconnected. This makes it possible for managers to pinpoint the underlying causes of problems and create long-lasting, practical solutions.
(ii) Improved decision-making: By taking into account the possible effects of specified choices on the system as a whole, stakeholders can make better decisions.
(iii) Improved communication and cooperation: The ideas of systems theory make it possible for the various parts of the company to work together and communicate openly.
(iv) Enhanced adaptability: Stakeholders can more effectively adjust to shifting market conditions and environmental changes by comprehending the dynamics of the business entity.
(v) Better organizational performance: Better and more sustainable overall performance is the outcome of a holistic approach to the entire system.

Sustainable decision-making, BPM, simulation, LCA, and RCM are the interrelated indicators in the conceptual framework. This article's introduction section provides a thorough discussion of LCA and RCM relative to the need for continuous assessments and improved decision-making. Providing highlights on BPM, sustainable decision-making in mining sectors, and simulation as a digital tool effective for data integration and efficient for the proposed LCA and RCM integration framework. An organization's business processes can be identified, discovered, designed, modelled, measured, analysed, monitored, improved, implemented, and optimized through the use of BPM. The objective is to attain consistent and focused outcomes that correspond with the established business strategic objectives. This frequently involves a mix of automated and manual tasks aimed at enhancing the efficacy and efficiency of various operational procedures. By enabling companies to record, track, evaluate, and optimize processes throughout the whole value chain, BPM promotes sustainability practices (Dumas et al., 2023). This facilitates decision-making by offering a transparent and unambiguous picture of an organization's operations. Additionally, this helps managers spot bottlenecks and comprehend how various business process components work together, allowing them to make well-informed decisions based on real-time data rather than conjecture, leading to more strategic and successful results. Increased visibility, data-driven insights, bottleneck identification, scenario analysis, and quicker response times are some of the other important value benefits of BPM in the context of sustainability and decision-making (Huy & Phuc, 2025).

In the literature (Pavloudakis et al., 2024) RCM is implied through the focus on optimizing mine equipment maintenance processes, enhancing operational efficiency, and ensuring safety in mining operations. The authors discuss the use of process mining techniques to improve maintenance, which aligns with RCM principles of maintaining system reliability while minimizing downtime. By integrating RCM methodologies, the mining industry can better manage risks, reduce environmental impacts, and support sustainable practices in mineral resource management. According to reports, the mining sector in South Africa is facing serious constraints in implementing its operational strategies (Sorensen, 2012). The mining sector in South Africa is used as a case study to investigate the rationale of this article.

Simulation can support more sustainable practices. Simulation provides a framework for simulating real-world systems or processes, enabling the assessment, investigation, optimization, and enhancement of complex systems or processes in a controlled setting. Opportunities for optimization, linked systems or processes, risk assessment, performance forecasting, data-driven decision-making, and digital twins are all made possible by simulation. For additional reading on simulation applications to decision-making, integration capabilities, and business process management, the works (Bisogno et al., 2016; Cimino et al., 2025; Heinrich et al., 2017) offer useful illustrations.

RESEARCH METHOD

The mixed approaches separated in the flowchart are illustrated in Figure 1. The steps in the diagram confirm the operationalization of the proposed integrated BPM-based LCA and RCM framework and how this combination influences the sustainability of the decision-making process.

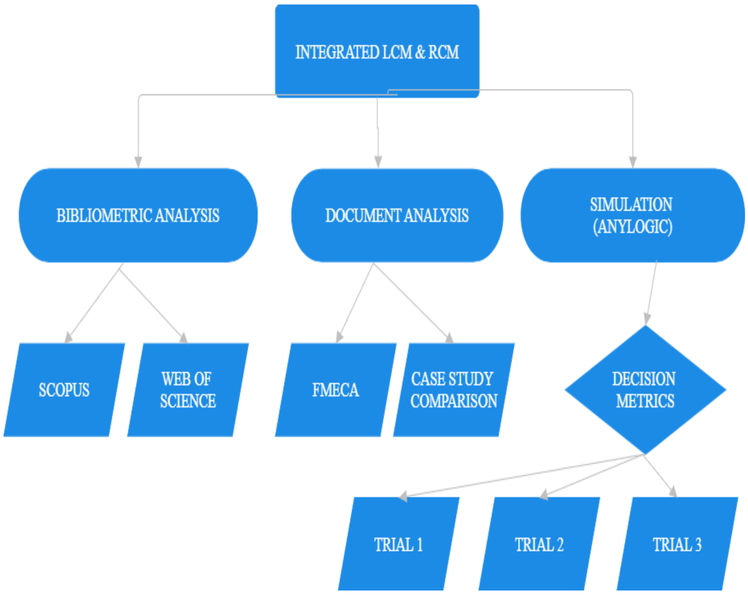

Figure 1. Flowchart of mixed-method approaches

The high-level objective of this article is to bridge LCA and RCM in the mining sector and explore how integrating the two, based on the management of business processes, influences the sustainability of decision-making. The proposed framework is multidimensional, taking into account the business processes of LCA and RCM to provide a more comprehensive assessment of the business impacts of the mining sector. The main components of the integration are captured in the flowchart.

Bibliometric analysis is a quantitative approach that uses statistical methods to analyze published literature (books, articles, etc.) to understand patterns, trends, and the impact of research within a specific field (Menesha & Mwanaumo, 2023). Bibliometric analysis provides an opportunity to review and compare the results with previous integrations of the LCA and the RCM. The Web of Science, Science Direct, and Scopus databases are among the most popular. However, the Scopus database and the Web of Science are the most widely used (Romero-Carazas et al., 2024). To carry out the bibliometric analysis in this article, the literature emerging on LCA and RCM research has been screened using the databases Scopus and the Web of Science.

FMECA is a risk management method used to develop a maintenance policy incorporating both qualitative analysis and quantitative aspects. Qualitative analysis is a method used to gather in-depth understanding and experiences, focusing on non-numerical data like text, audio, or visual materials to explore concepts, opinions, or experiences. It's particularly useful for understanding the "why" and "how" behind a phenomenon (Parilla & Evangelista, 2025). Quantitative research is a systematic investigation that uses numerical data and statistical analysis to quantify opinions, behaviors, and other defined variables. It aims to establish relationships between variables and generalize findings to broader populations. The FMECA approach involves analyzing the legacy of the RCM procedures in the mining sector as a case study. Further analysis, comparing the results of the case study with standard maintenance practices, is recommended for the interruption of the warranty period. The documents processed for analysis include checklist reports and casualty reports on the equipment. This information can be obtained from the Computerized Maintenance Management System (CMMS), and the digital platform available to the mining industry is used as a case study. Some of the tests performed include time to failure (TTF), Pareto-Haus test, null hypothesis, Weibull distribution, Chi-squared test, maximum likelihood estimate (MLE), and distribution plots to estimate the reliability or durability of the device. The Minitab 21 statistical tool is used to analyze the results of the test.

The rapid development of new technologies in the modern era has resulted in the creation of a wide variety of tools that assist humans in completing their work (Chandra et al., 2023). The simulation tool is one of these new technologies. The simulation approach provides a pilot test to demonstrate the applicability of the decision-support framework in practice and the relevance of this framework to sustainability. A simulation tool may be used to model and observe complex systems in the real world, and to predict how well the system is likely to perform. To achieve optimal scenarios that are easy to communicate, validate, and understand, the simulation architecture can compare and quantify alternatives to a design challenge by using its predictive capability. AnyLogic simulation software is used to record, explore, and model the processes involved in the proposed LCA and RCM business process model. A similar development and prioritization scenario using the AnyLogic simulation software is detailed in the literature (Cherednichenko et al., 2025; Zhou et al., 2021). To facilitate the simulation decision-making scenario, the first step is to configure the business processes of the LCA and the RCM. Decision metrics or relevant measurement parameters facilitating the scenario impact assessment of the proposed framework will then be decided upon. The configured simulation framework is then repeated in various experiments to see how each of the measured parameters affects the defined response variable.

Each method outlined in the summary outlines the main dimensions, strategies, and tools used for development to be integrated and contributes to a more complete understanding of the objective of this article. The integration or operationalization process shall be developed based on system theory, ensuring that the various elements of the proposed model are not considered separately but as integral parts of a whole. This includes ensuring that data from different sources are combined to produce a more comprehensive overview.

Case study selection criteria

This sub-section elucidates the rationale behind the selection of research methodologies aimed at establishing credibility and facilitating reproducibility. This manuscript investigates the capabilities of business process management in the context of sustainable life cycle assessment and decision-making implementations grounded in reliability-centered maintenance. The chosen mining enterprise was selected due to its representation of a mid-sized operation situated within the densely populated suburb of Johannesburg, South Africa, and its utilization of Failure Mode, Effects, and Criticality Analysis (FMECA) as the developed framework for its Reliability-Centered Maintenance (RCM) process, thereby enabling comprehensive analysis and application of mining equipment that has undergone RCM protocols. The selected mining enterprise distinctly aligns with the parameters of qualitative research methodologies. Several of the criteria are enumerated:

(i) The chosen case study serves as an exemplary representation of the demographic within the mining industry that is under examination. This selection was predicated upon a rigorous evaluation of criteria scoring and the availability of data pertinent to mining enterprises employing FMECA methodologies in the Republic of South Africa, informed by an initial review of industry documentation.

(ii) An initial review of the industry documentation suggests that the chosen case study conforms to the established theoretical framework devised for this research. The organization is congruent with the resource-based perspective of FMECA, yielding substantial insights into optimal practices associated with FMECA, and it has exhibited innovative responses to regulatory pressures concerning FMECA-related issues.

(iii) Access to internal data and engagement with stakeholders were facilitated, thereby enabling a thorough data collection process that might not be achievable with alternative mining enterprises.

(iv) The authors recognize that this unique approach limits the scope of application, but allows an in-depth understanding of FMECA best practices and innovative regulatory pressures related to FMECA concerns. Future research could be extended to comparisons at multiple sites.

Scope of data used

Data from the investigation included qualitative (bibliometrics) and quantitative sources (FMECA and simulation). The FMECA data are based on archives of maintenance sustainability reports and operational metrics between 2015 and 2024, focusing on the core activities of FMECA, and are consistent with research objectives to capture historical trends in mining practices and measurable sustainability indicators of FMECA. Data scope was limited by access restrictions, as all data related to the mining company of the case studies were anonymized according to ethical guidelines. The combination of the data field, the quantitative source (bibliometrics), and the quantitative source (FMECA and simulation), reduces biases and improves the credibility, validity, and strength of research results. Triangulation refers to the use of multiple methods, sources of data, theories, or investigators in a study to cross-check the results. In this study, we used methodological triangulation to combine bibliometrics (quantitative analysis of literature patterns), FMECA (failure mode, effects, criticality analysis, structural risk assessment technique), and simulation (model scenarios to predict results). This approach is validated in new publications as particularly useful in interdisciplinary fields such as engineering, management, and innovation research, where the methods can complement each other: library metrics provide historical and trend-based insights, FMECA qualitative/quantitative identifies potential failures and risks, and simulation tests hypotheses under controlled variables. Bibliometrics can ignore contextual nuances that FMECA can address; simulation validates FMECA outputs empirically.

Reliability and validity

Triangulation improves overall reliability and effectiveness. If bibliometrics identify high-citation risks (e.g., common failure modes in literature), FMECA critically identifies these risks, and simulations confirm their probabilities, and consistency across methods indicates reliable data. If there are discrepancies, it signals areas of improvement, such as the recalibration of simulation parameters. This repeatability increases reliability by repeating simulation protocols and ensuring that each iteration is documented in the experiment. For validity, triangulation ensures a comprehensive coverage, bibliometric validation ensures external relevance (external validity), FMECA ensures internal logic (internal validity), and simulation tests applicability (ecological validity). A single method can disperse the results (e.g., bibliometrics favours popular themes), and triangulation counteracts this. For example, if FMECA highlights niche risks not in the literature, simulation will verify their actual impact. This contributes to a certain reduction in biases and further validation or strengthening of results. Despite the effectiveness of the triangulation method to strengthen the study, the authors acknowledged certain deficiencies in the instrument. Each method has inherent limitations, and even if combined, they are still persistent. The authors first outline the main limitations of each method and then summarize its integration into triangulation.

Bibliometrics

(i) Incomplete coverage: Biased or insufficient data may result from databases like the Web of Science and Scopus, which were employed in this work, frequently excluding non-journal formats, certain disciplines, geographical areas, languages, or developing topics.
(ii) Quantitative emphasis over quality: Metrics such as citation counts or h-index quantify influence by number, but they disregard context (such as negative citations), content quality, or societal relevance. They can also be manipulated by citation cartels or self-citations.
(iii) Temporal and disciplinary biases: metrics favor established work, which disadvantages new or multidisciplinary research, and citation methods differ between disciplines (medical vs. humanities, for example).
(iv) Subjectivity and gaming: Metrics are not good for individual evaluations in comparison to qualitative expert review; they are susceptible to artificial inflation and fail to capture subtle scholarly influence.
(v) Lack of causal insight: Provides descriptive patterns but not explanations for trends.

FMECA

(i) Subjectivity and variability: Because Risk Priority Numbers (RPNs) depend on expert assessments of severity, occurrence, and detectability, the results may differ depending on the makeup of the team.
(ii) Time and resource-intensive: For complicated systems, it necessitates a thorough system breakdown and workshops, which adds to the labour and expense.
(iii) Limited scope: focuses on individual failures; has trouble with human-software interactions, numerous concurrent failures, or emergent behaviours; frequently offers optimistic reliability estimates.
(iv) Mathematical errors: Without taking interdependencies or dynamic situations into account, RPN computations (such as the product of scores) may overemphasize or underemphasize dangers.
(v) Static nature: Ignores unknowns or changing risks in real-world applications, assuming known failure mechanisms.

Simulation

(i) Assumption dependency: Models are simplifications based on assumptions that may not hold in reality, which can lead to inaccurate predictions if the data is incomplete or flawed.
(ii) Data and computational demands: High-quality input data is essential; poor data results in unreliable outputs. Additionally, complex models are computationally intensive and difficult to interpret.
(iii) Approximate results: The outputs are probabilistic approximations rather than precise answers; they are sensitive to uncertainties and cannot be easily transferred across different problems.
(iv) Over-simplification risk: Achieving a balance in complexity is challenging; overly simplistic models may overlook key dynamics, while overly complex models can become opaque or unmanageable.
(v) Validation issues: It is difficult to verify models against real-world scenarios, particularly for rare events or long-term predictions.

Combining bibliometrics, FMECA, and simulation in a research article can uncover patterns (through bibliometrics), evaluate risks (through FMECA), and test scenarios (through simulation), yet this process has its drawbacks. These drawbacks arise from the incompatibilities of the methods, the demands on resources, and the challenges of integration:

(i) Resource intensity and complexity: Triangulation increases the time, cost, and expertise required. Bibliometrics necessitates data mining skills, FMECA requires domain-specific knowledge for risk assessment, and simulation demands programming and computational resources. In small-scale studies or resource-constrained research articles, this can result in incomplete synthesis or superficial integration, rendering the process impractical for individual researchers or those facing tight deadlines.
(ii) Potential for inconsistent or contradictory results: The methods function on different paradigms. Bibliometrics is retrospective and descriptive, FMECA is qualitative-quantitative and focused on failures, while simulation is predictive and model-based. Discrepancies (for instance, bibliometric trends not aligning with simulated outcomes) may occur, necessitating reconciliation that could reveal flaws in one method, incomplete theories, or gaps in data. In the absence of clear resolution strategies, this undermines confidence in the overall findings.
(iii) Integration and interpretation challenges: Combining outputs presents complexities. For example, bibliometric citation data may provide insights into FMECA failure modes; however, incorporating them into a simulation model necessitates assumptions regarding causality, which could lead to oversimplification or bias. Qualitative factors (e.g., FMECA assessments) might conflict with quantitative factors (e.g., simulation probabilities), resulting in subjective interpretations. In research publications, this can lead to inflated or ambiguous reporting if not organized properly.
(iv) Bias amplification or masking: Although triangulation seeks to minimize bias, it can inadvertently introduce new biases if the methods employed are not uniformly rigorous (e.g., subjective FMECA ratings affecting objective simulation inputs). Furthermore, it may obscure fundamental issues, such as common data limitations across methodologies, creating a misleading sense of validation.
(v) Scalability and generalizability issues: Effective for specific, clearly defined challenges (e.g., risk in engineering systems), but less effective for broader or dynamic phenomena where scales vary (e.g., bibliometrics on global trends versus simulation of localized failures). Findings may not extend beyond the context of the study, restricting wider applicability in research articles.
(vi) Ethical and practical constraints: In disciplines such as engineering or healthcare, ethical considerations in simulation (e.g., modeling human factors) or FMECA's dependence on proprietary data can limit triangulation. Moreover, excessive reliance on models may disconnect findings from real-world validation, as triangulation cannot replace empirical verification.

Despite these challenges, the triangulation approach utilized in this study can provide deeper insights when applied thoughtfully. To address these limitations in the current work, the authors:

(i) Clearly justify the choice of methods based on the specified research question.
(ii) Employ structured frameworks (e.g., sequential triangulation where bibliometrics informs FMECA, which in turn informs simulation).
(iii) Disclose uncertainties such as confidence intervals in bibliometrics.
(iv) Validate integrated results against external data where possible.

FINDINGS AND DISCUSSION

The search parameters and filters for the bibliometric analysis are outlined:

(i) The selected refined keywords are: "LCA*" AND "RCM*" AND "Mining*" OR "mining*"; "lca*" AND "rcm*" AND "Mining*" OR "mining*"; "Life Cycle Assessment*" AND "Reliability Centered Maintenance*" AND "Mining*" OR "mining*"; "life cycle assessment*" AND "reliability centered maintenance*" AND "Mining*" OR "mining*". The asterisks (*) are used to ensure the search includes loose phrases.

(ii) English documents only are used. Evidence indicates articles published in English have a higher number of citations in comparison to publications in other languages.

(iii) All document types are selected, including journals, conference papers, proceedings, book chapters, and other non-refereed publications. Both Journals in Final and in Press are selected.

(iv) All subject areas provided in the Scopus and Web of Science databases are included in the search.

(v) No date boundaries screened for the search.

No documents were found from the defined keyword search using both the Scopus and Web of Science databases. This reinforces the need for stakeholders in the mining sector to conduct research that integrates LCA and RCM operational protocols. The authors decide to refine the search keywords to LCA and RCM in silos to gather information on funding institutions supporting LCA and RCM research. A relatively high number of funding institutions that sponsor proposals for research based on LCA or RCM techniques are found. Figure 2 shows the ten institutions at the top of the hierarchy. The findings provide guidance and an edge to future researchers seeking funding for research in this area.

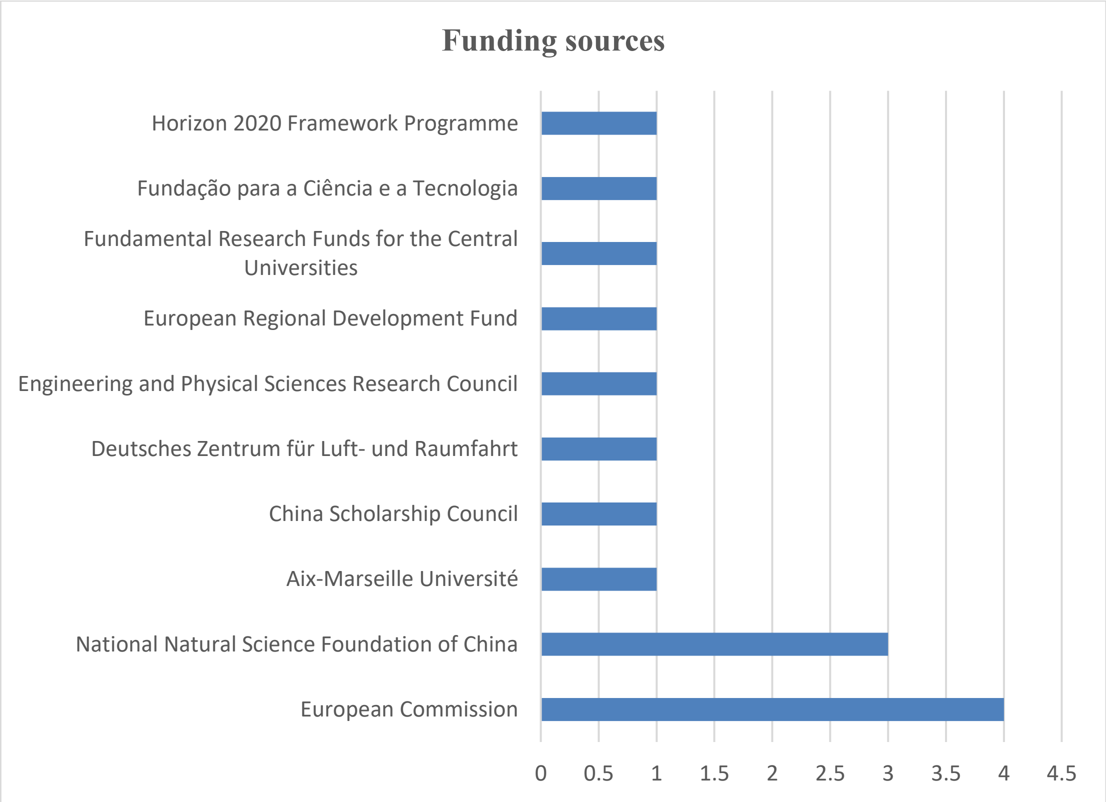

Figure 2. Funding sources

This "funding sources" bibliometric search is done to monitor the impact of research that the institution funds and to make well-informed decisions about future funding allocations. Here, the research pertains to the mining and manufacturing industry. To improve their chances of receiving funding, the choices may involve making sure that research proposals are relevant, rigorous, and of high quality.

The mining company selected as a case study uses FMECA as its developed RCM process. Mining equipment is generally broad, to narrow down and enhance the analysis and application of findings. The focus is limited to systems that have been subjected to the RCM procedures. Figure 3 shows the output of the rating of the system criticality divided into seven components. System criticality is achieved through a systematic process consisting of the identification, evaluation, and classification of components according to their impact on production, safety, and costs. This helps prioritize maintenance efforts, optimize resource allocation, and minimize interruptions by ensuring that critical components receive the attention they require.

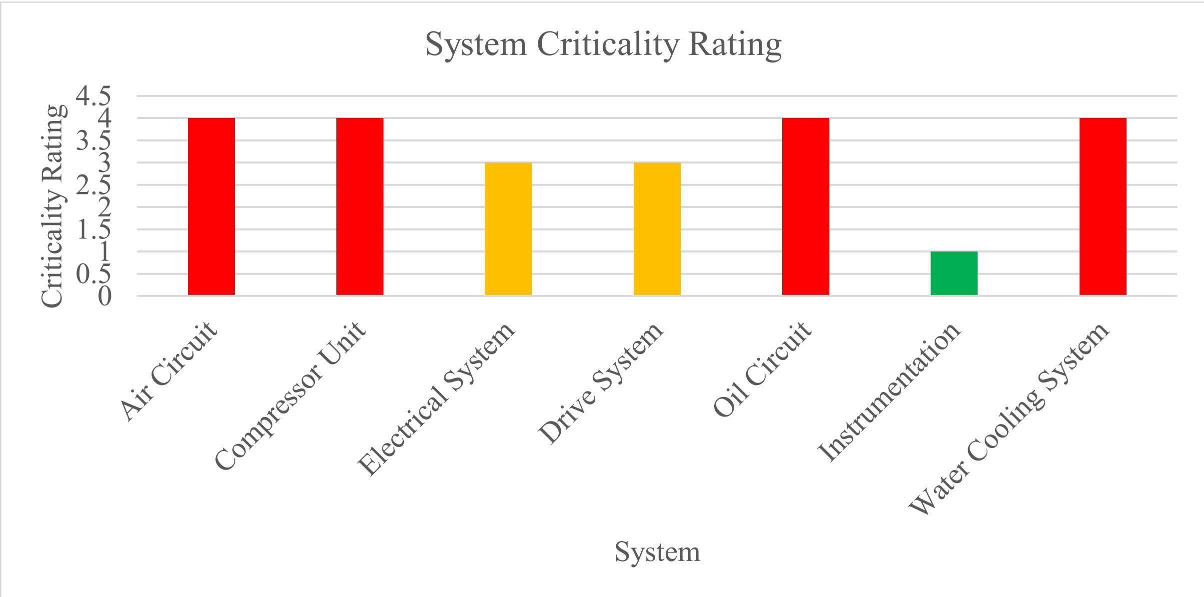

Figure 3. System criticality rating

When FMECA is deployed, a maintenance strategy breakdown is performed to determine if the mining RCM process is in line with industry best practices. Figure 4 indicates what the results look like.

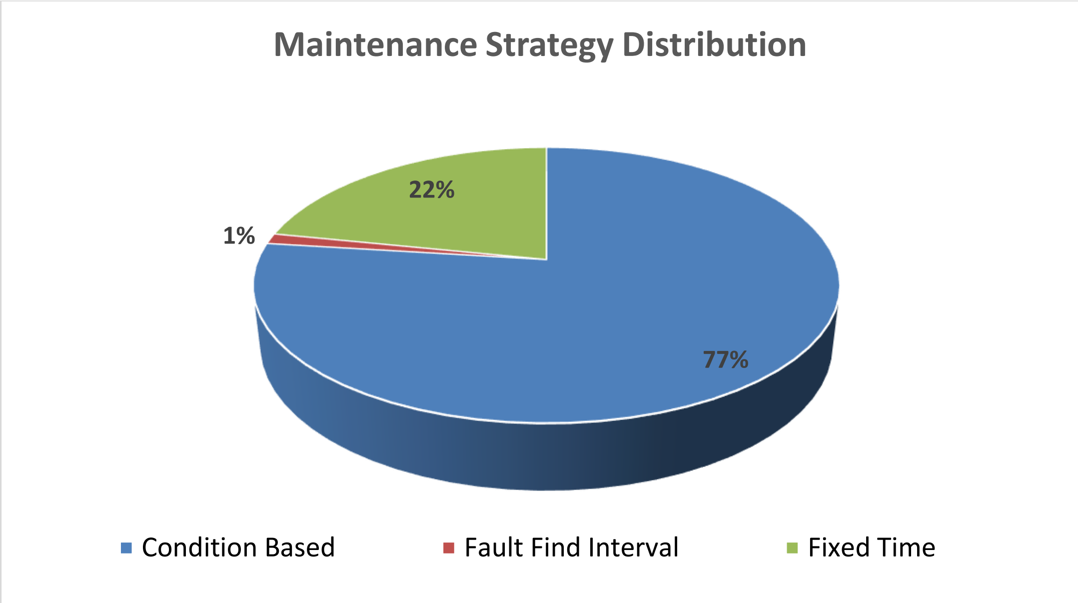

Figure 4. Distribution of FMECA maintenance strategies

The number of primary predictive tasks for each system is estimated to determine if the use of resources, in this case, labour and time, corresponds to the criticality of the system. Figure 5 indicates what the outputs looked like.

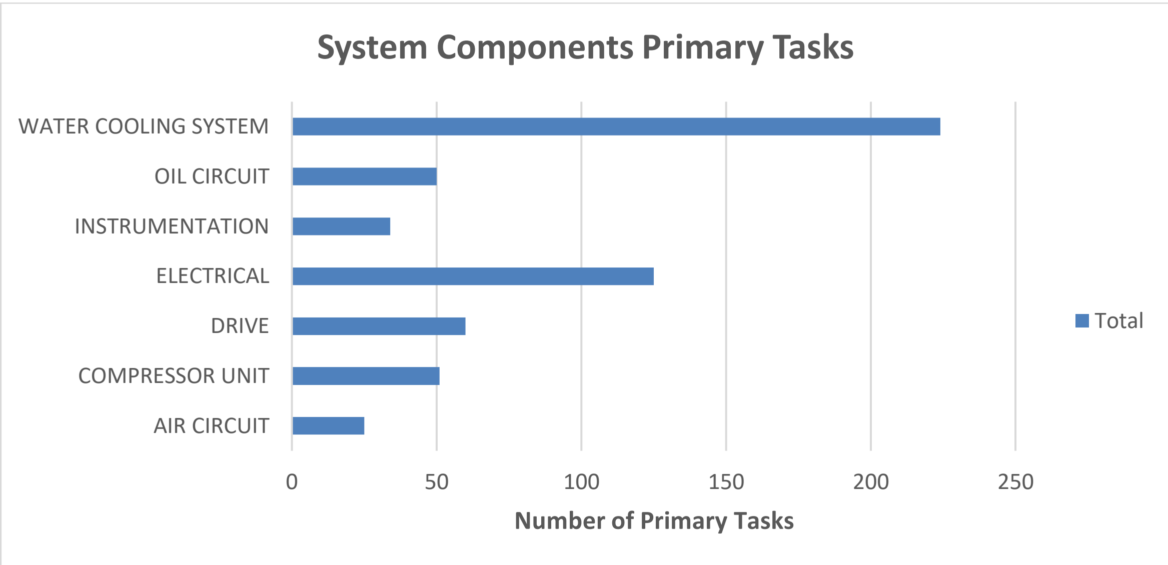

Figure 5. Number of primary tasks per system, represented by a graph

For the determination of the case study performance with global maintenance practices, statistics on equipment failures from 2017 to 2023 are used. In 2018, the RCM process was developed and deployed, and paper-based MWOs are in use. In 2021, the digital work execution platform for RCM operations was launched. For the analysis of reliability data, the Minitab 21 statistical analysis tool is used. The first step is to use trend and cumulative correlation tests to determine if the data are independent and statistically clustered. Figure 6 indicates the plots.

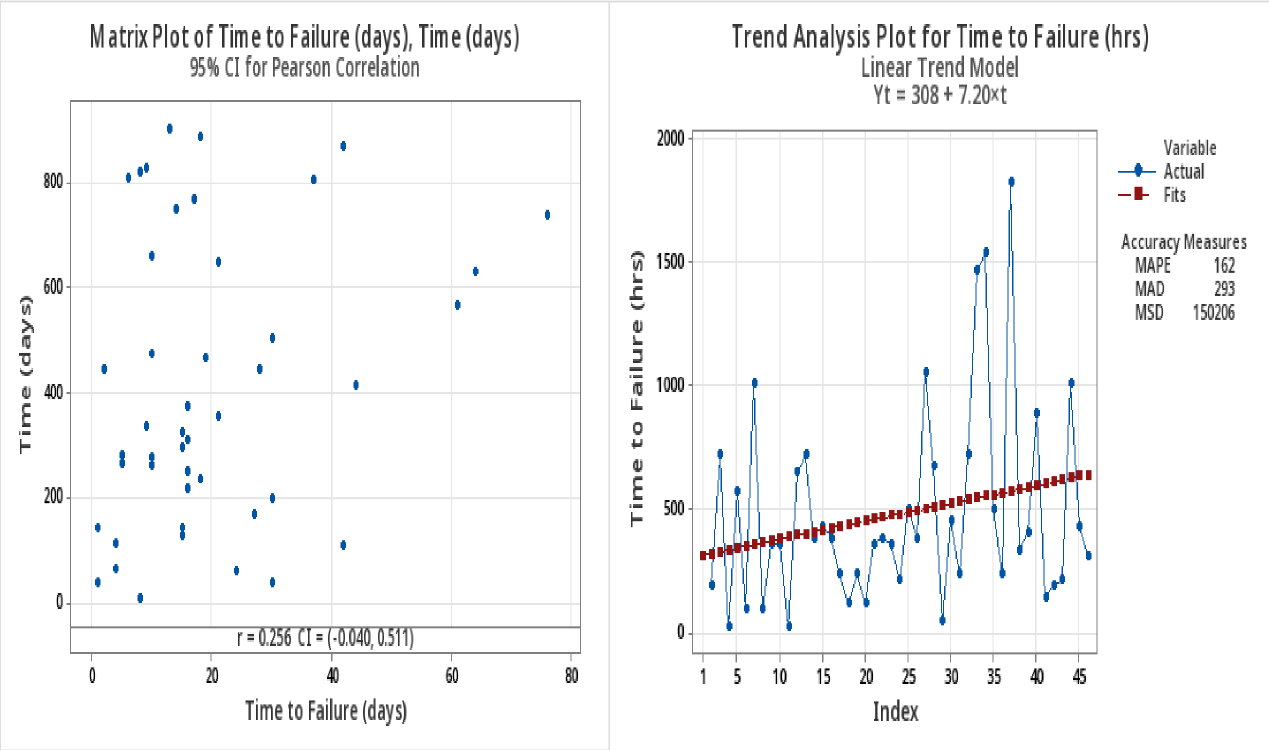

Figure 6. Serial correlation and data trend tests

The Pareto principle, which states that a small number of failures is caused by a large number of failures, is applied as a first step in the analysis of reliability data. By examining the data on failures, it is possible to identify the most cost-effective way of dealing with the highest percentage of failures. The Pareto diagram of system failures is illustrated in Figure 7. The most important system, according to the graph, is the drive system, which accounts for 40 percent of the breakdowns.

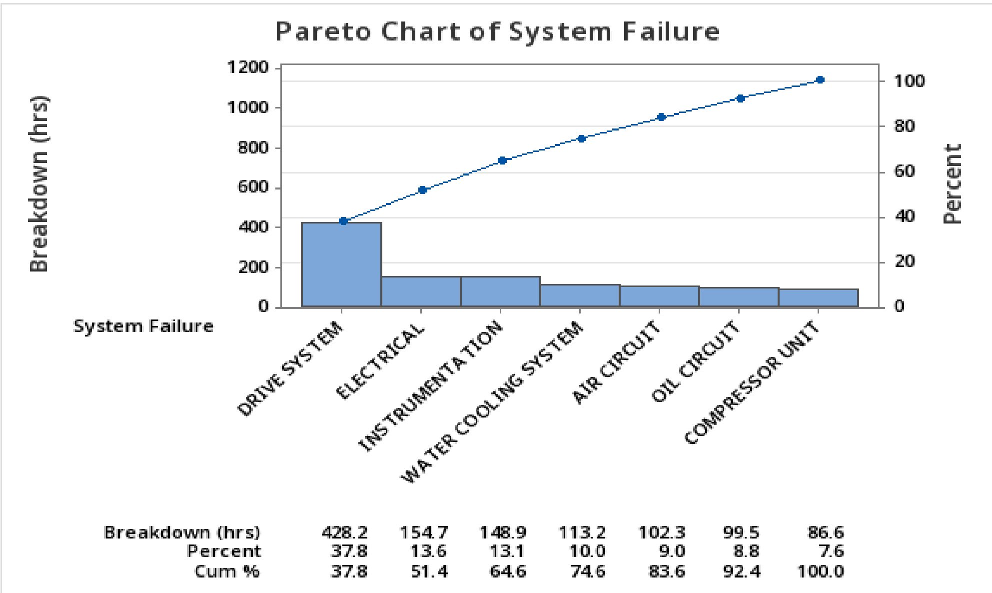

Figure 7. Pareto chart of failures in systems

Equipment failure data is categorized into two periods:

(i) RCM implementation using paper-based MWO 2017 - 2020
(ii) RCM implementation using a digital work execution platform, 2021-2023.

Breakdowns from 2017 to 2020 are shown in Figure 8, and breakdowns from 2021 to 2023 are shown in Figure 9.

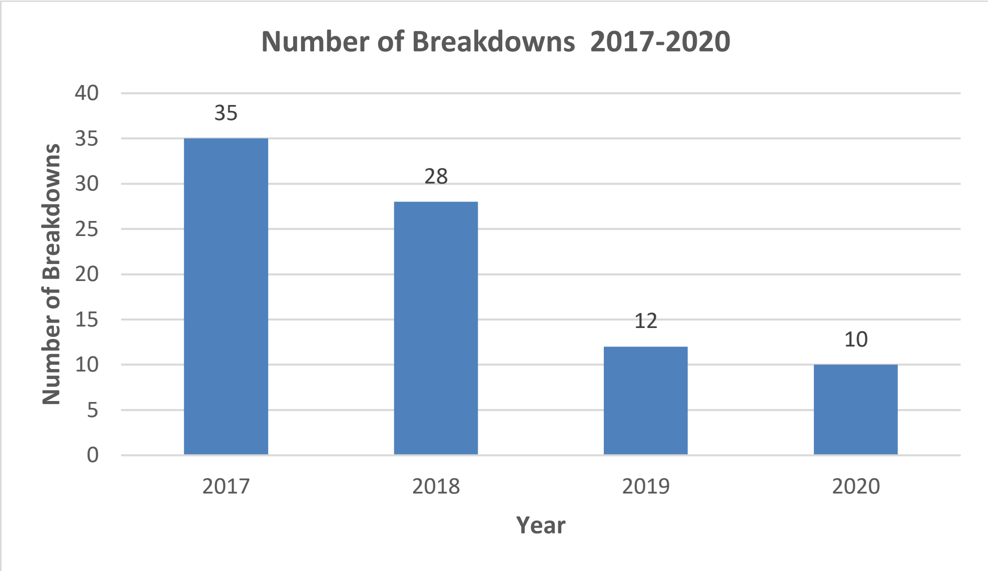

Figure 8. Number of breakdowns pre- and post-RCM implementation using a digital platform

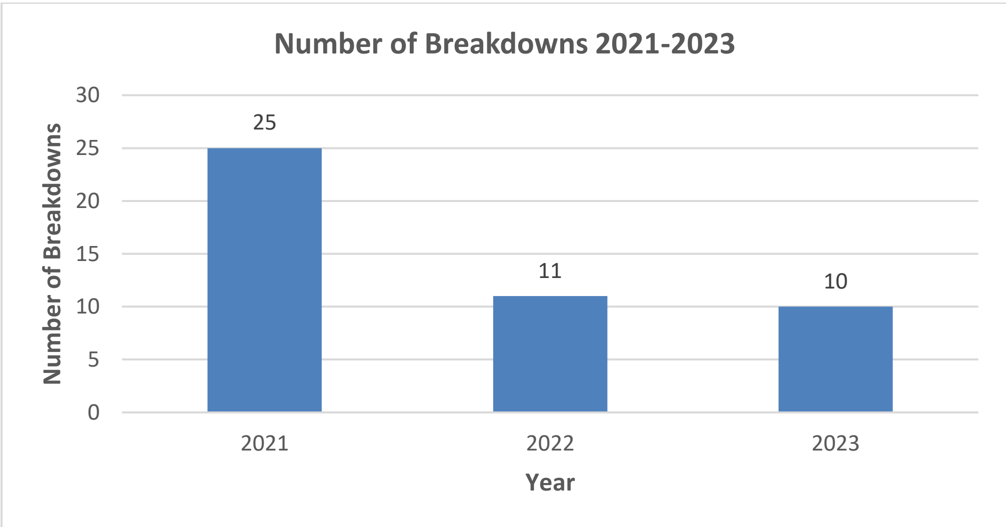

Figure 9. Number of breakdowns post-RCM implementation using a digital platform

Weibull analysis, available in Minitab 21 software, is used to interpret the durability of appliances. This is for assessing the reliability of the equipment. The goodness of fit test is conducted in Minitab 21 by the Chi-squared method to determine how well the collected failure data fits the Weibull distribution (null hypothesis). Maximum likelihood estimates (MLEs) are considered a reliable method to estimate the volatility of a parameter. The MLE parameter is used to estimate Weibull distribution parameters over different periods. These plots are reflected in the report figures 10 and 11.

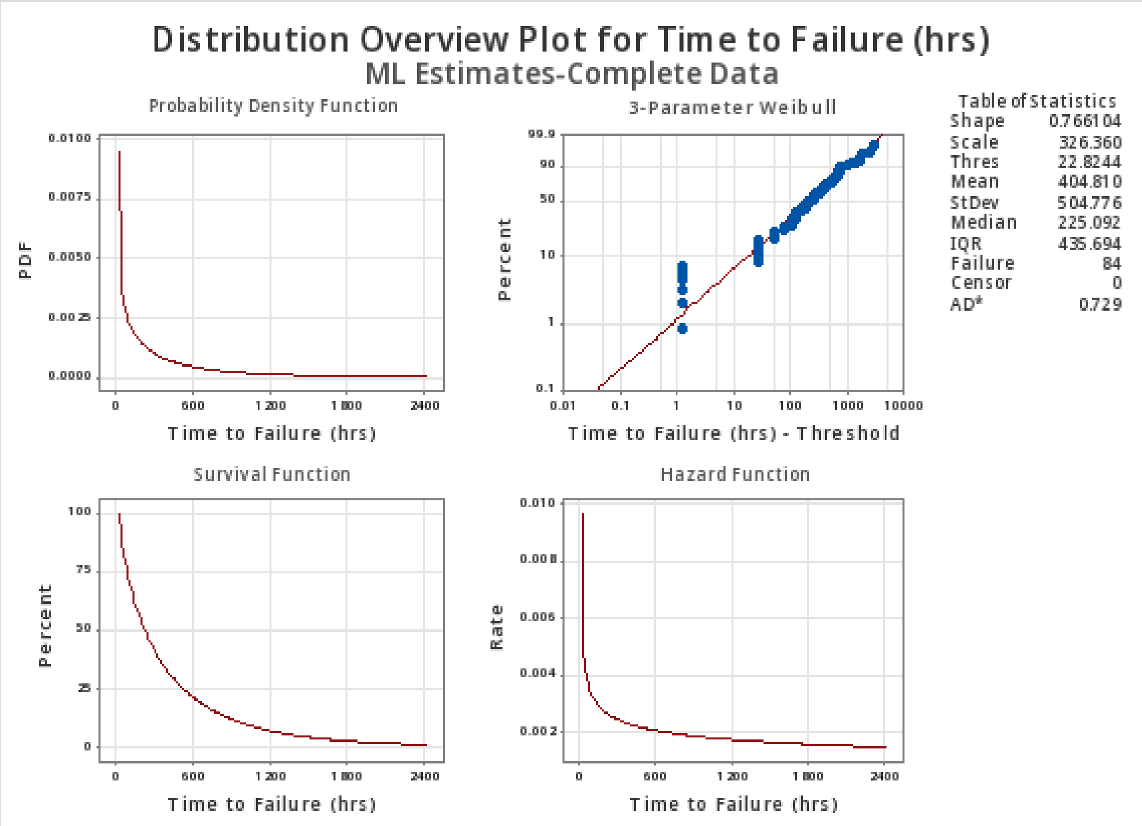

Figure 10. MLE parameter for Time to Failure (TTF) data using paper-based MWO from 2017 to 2020

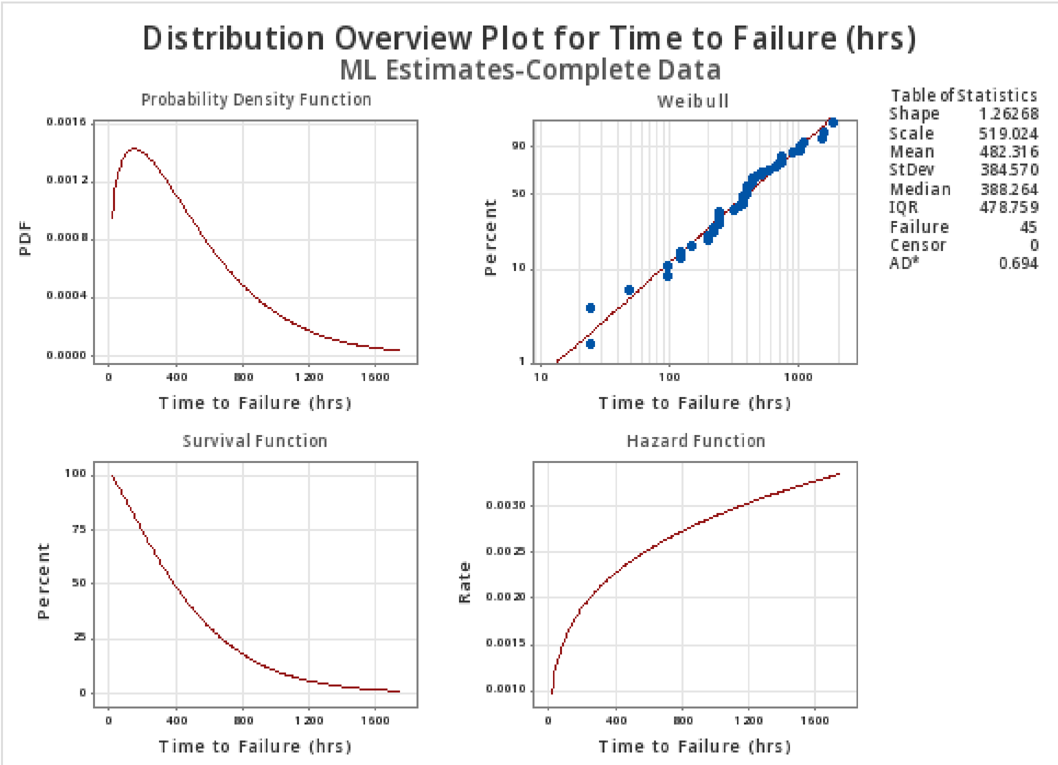

Figure 11. MLE parameter for TTF data using the digital work execution platform from 2021 – 2023

As shown in Figures 10 and 11, the average time to failure is 404 and 481. Figure 12 shows the Weibull distribution plots for the two comparison periods.

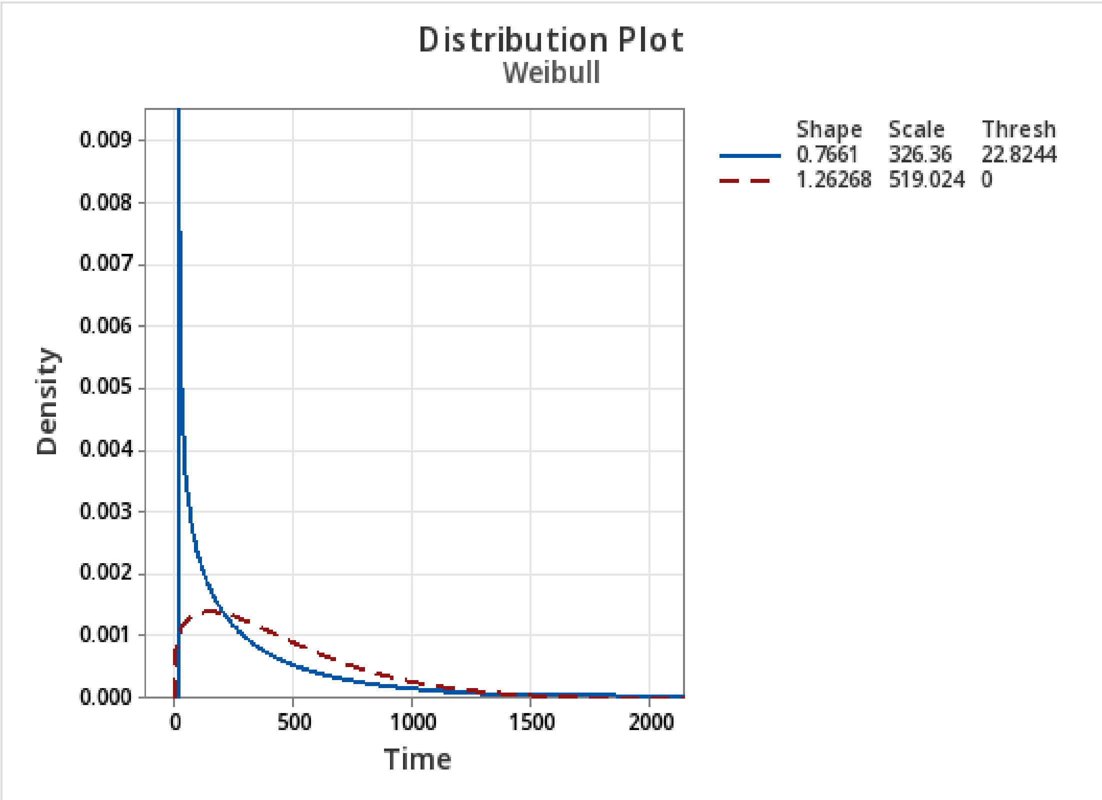

Figure 12. Weibull distribution plots before and after the digital platform for RCM implementations

The FMECA complements the evaluations provided in this article with qualitative information on the process of operationalization of the proposed integrated framework. FMECA provides data on possible failure modes, their effects, and the criticality of each component. This analysis enables active risk mitigation leading to improved reliability, safety, and operational efficiency in the mining environment.

The simulation approach provides pilot tests to demonstrate the applicability of the decision-support framework in the real world and the relevance of this framework for sustainability. To facilitate the simulation decision-making scenario, the first step is to configure the business processes of the LCA and the RCM. Decision metrics or relevant measurement parameters facilitating the scenario impact assessment of the proposed framework will then be decided upon. The configured simulation framework is then repeated in various experiments to see how each of the measured parameters affects the defined response variable.

The document analysis section confirms that FMECA is the developed RCM process used by the mining company, which was chosen as a case study. Figure 13 is a standard FMECA flow chart taken from the literature. (Balaraju et al., 2019).

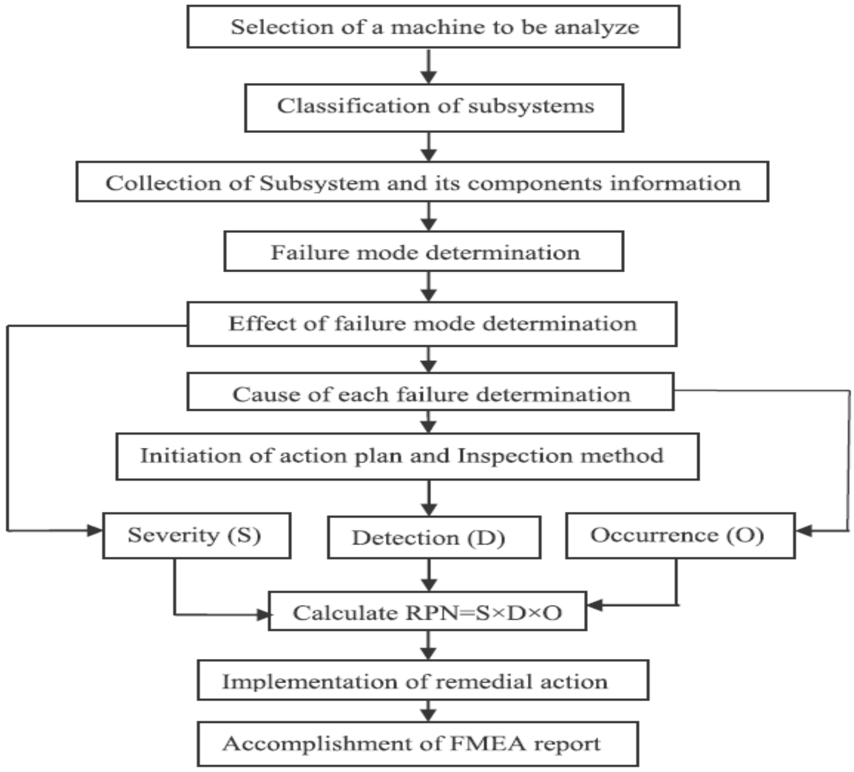

Figure 13. FMEA analysis flow chart adopted from the research (Balaraju et al., 2019)

The LCA frameworks are divided into Social Life Cycle Assessment (SLCA), Environmental Life Cycle Assessment (ELCA), and Economic Life Cycle Assessment (ECLAS). These LCA frameworks can be assessed in four phases: the definition of objectives and scope; the Life Cycle Inventory (LCI); the Life Cycle Impact Assessment (LCIA); and Interpretation. (Arvidsson & Ciroth, 2021). To develop the proposed integrated framework and the pilot test demonstrations, the LCI flow process is used to present a case study of how RCM failure modes directly inform LCA parameters. This is achieved by combining both the FMECA analysis flow chart and LCI flow process as one integrated unit in the design of the simulation architecture. Figure 14 is a flowchart of the LCI process as adopted from the literature. (Arvidsson & Ciroth, 2021).

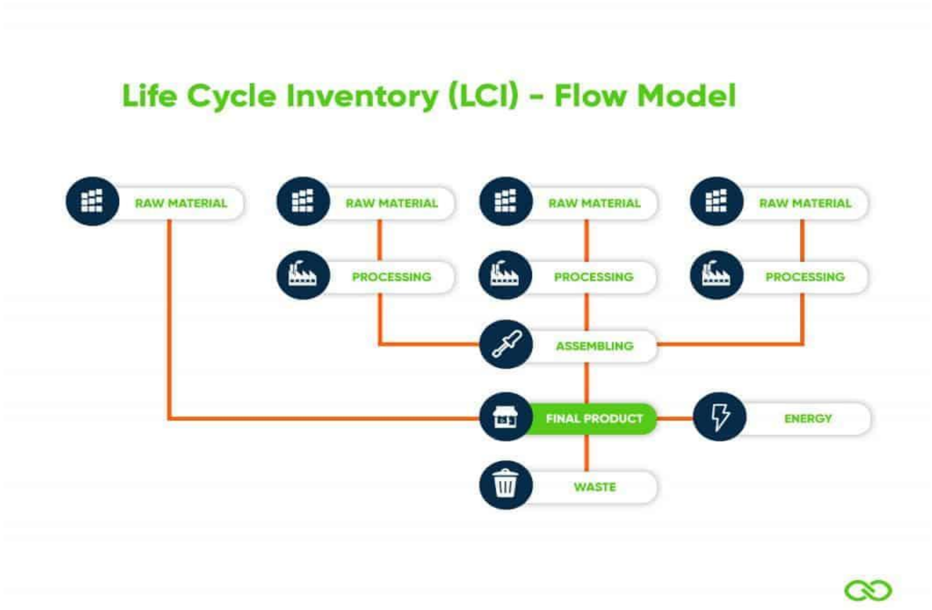

Figure 14. LCI flow process adopted from the work (Arvidsson & Ciroth, 2021)

Decision metrics or relevant measurement parameters

After the decision and configuration of the business processes of the LCA and RCM, the next step in the design of the simulation architecture is to define the relevant measurement parameters of the LCA and RCM to facilitate the scenario impact assessment of the proposed framework. The introduction section, "research gap" of this article, explains cost considerations and how data integration facilitates the linkages between LCA and RCM. However, this article concentrates on data integration through business processes.

Combined LCA and RCM data can be integrated into a model. Time resources, such as turnaround time (TAT), are often used as a metric to assess performance and to quantify the time between the start and the end of a process. TAT is considered appropriate to present case study scenarios to design the simulation architecture. TAT is a key metric used in various sectors to measure efficiency, customer satisfaction, and productivity, with application scenarios in logistics, manufacturing, customer service, testing in the laboratory, and the IT sector (Febrian et al., 2024). The following measurement parameters and numerical values, derived from a combination of various sample models provided in the AnyLogic simulation architecture, are used to configure the LCI and RCM simulation architecture for the measurement of TAT in any business flow diagram. Deduction parameters are set to allow a feedback loop of deduction of the theorem, and present a scenario example to assess the robustness of the model. The measurement parameters, as reflected in the numerical values of maximum average process flow "105", maximum process flow rate "0.06", process efficiency "0.165", and total number of processes "3,500", are taken as an example of the simulation settings to represent real-world values.

A modeling and simulation technique called system dynamics uses sets of conceptual tools to help design and comprehend the structure or dynamics of complex systems in the real world. The identified decision metrics and parameters represent the system's outputs together with inputs and are captured as stocks and flows, ensuring that dependency and alternative parameter scenarios are considered in the configuration. To allow for effective considerations of the dependencies, the systems dynamics of the combined simulation data gathered are considered. According to (Hashemizadeh et al., 2024) Systems dynamics is a useful method for research examining causal dependencies in systems. Figure 15 captures LCI and FMECA process flows combined with decision metrics and parameters configured in a simulation architecture using the AnyLogic software.

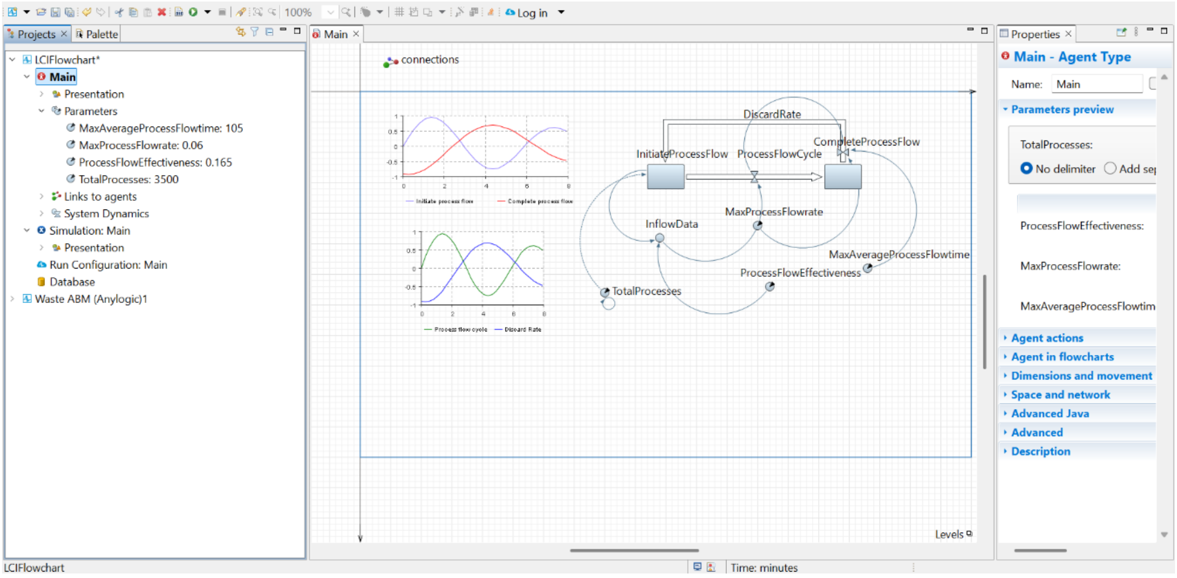

Figure 15. Simulation architecture using AnyLogic software

Experimental framework

To allow dynamic interactions or an experimental framework of integrated metrics, the configured simulation framework is repeated in different experiments to see how each parameter measured affects the defined response variable. The business execution scenarios are set to be quantified with a maximum (+0.1), a normal, and a minimum (-0.1) business state. Where normal is assumed to be the standard condition for the measurement parameters, maximum and minimum values are accepted as ranges of limits to facilitate the comparison of the parameters. For simplicity of the experimental framework, the parameters identified as the independent parameters are given acronyms. Where "maximum average process flow time (105) = A; maximum process flow rate (0.06) = B, process efficiency (0.165) = C, and the total number of processes (3500) remains constant during iterations. After completing the simulation architecture configuration, the model is iterated and set at a normal business state to test its effectiveness in conducting experimental scenarios. Figure 16 depicts a thin-slice architecture of the framework in a business-normal state.

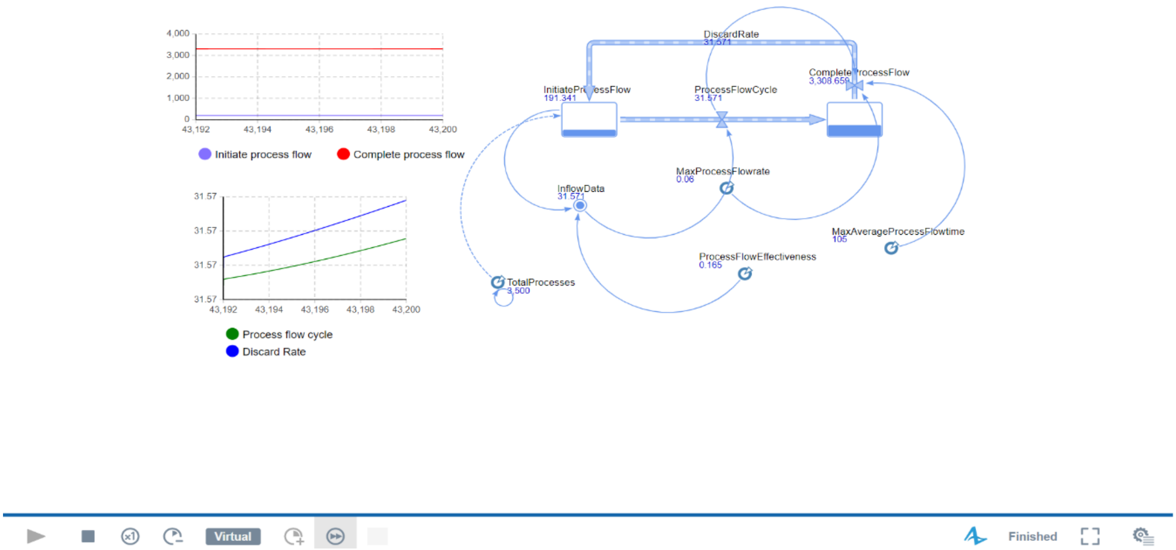

Figure 16. Thin-slice architecture during iteration for the measurement parameters at a business normal state

Simulating experiments investigate the effects of one or more factors (independent parameters) simultaneously and investigate the possible interactions between these factors. This can be one or more combinations. This design determines effectively if the impact of one parameter is dependent on the level of another, and how each of the parameters affects the dependent one. The seven single, double, and triple combinations that can be obtained by the three alternative parameter constraints selected in this article are: A, B, C, AB, AC, BZ, and ABC. Simplified single (experiment 1), double (experiment 2), and triple (experiment 3) scenarios are used for the iterations. To determine the TAT of the optimized full process flow, the single, double, and triple scenarios shall initially be reverted to normal, and then revised to a minimum or maximum. Replication is the practice of repeatedly applying the same experimental conditions in simulated experiments. This reduces the possibility of random errors and helps to guarantee the reliability of the results. In this article, each experiment is repeated three times, and after three replicates, the average numerical value of the iterations is taken into account.

Experiment 1

Researchers can independently investigate, using simulation models, the effect of each of the three parameters (A, B, and C) on the response variable or the dependent variable (TAT). This is more efficient as it can be completed in a single set of trials rather than in separate trials for each parameter by changing each parameter separately. By setting each parameter to either maximum or minimum, the individual experiment made modifications gradually. The results are presented in Table 1 and Figure 17.

Table 1. Single combination

	Maximum	Normal	Minimum
A	**2243 (1.45%)**	**2211**	**2170 (-1.85%)**
B	**2210 (-0.05%)**	**2211**	**2212 (0.05%)**
C	**2232 (0.95%)**	**2211**	**2186 (-1.13%)**

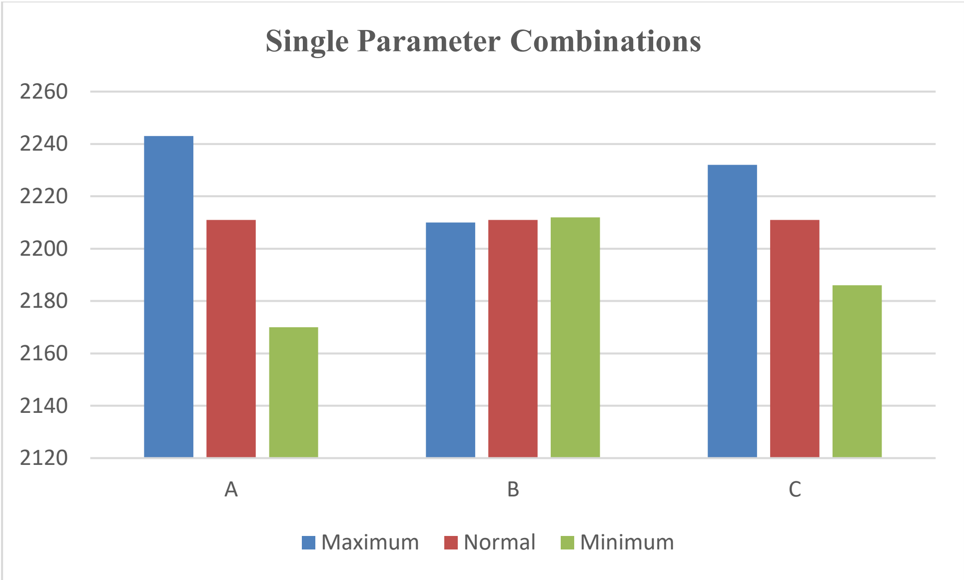

Figure 17. Single-parameter iterations

The following deductions are described with one measurement parameter changed once at a time:

- The measurement parameter maximum average process flowtime (A) increases the TAT of the business by (1.45%) when set at maximum and reduces by (-1.85%) when set at minimum. This implies that more total processes are completed when the measurement parameter maximum average process flowtime (A) is set at maximum.
- The measurement parameter maximum process flow rate (B) decreases the TAT of the business by (-0.05%) when set at maximum and increases by (0.05%) when set at minimum. This implies that more total processes are completed when the measurement parameter, maximum process flow rate (B), is set at a minimum.
- The measurement parameter process flow effectiveness (C) increases the TAT of the business by (0.95%) when set at maximum and reduces by (-1.13%) when set at minimum. This implies that more total processes are completed when the measurement parameter process flow effectiveness (C) is set at maximum.

Experiment 2

The identification of interaction effects is a major advantage of simulation design. This occurs when the effect of another factor on a dependent variable varies depending on its level. One by one, the double-track altered two parameters that had been set to the maximum or minimum to allow this. Results are presented in Table 2 and Figure 18.

Table 2. Double combination

Double	**Max**	**Normal**	**Min**
AB	**2243 (1.45%)**	**2211**	**2170 (-1.85%)**
AC	**2264 (2.40%)**	**2211**	**2141 (-3.17%)**
BC	2233 (0.99%)	**2211**	2186 (-1.13%)

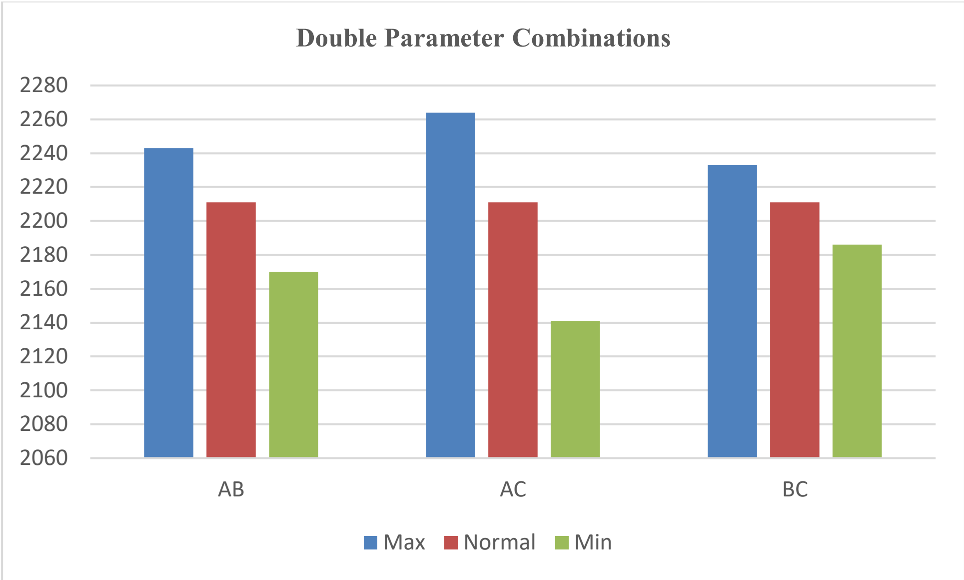

Figure 18. Double-parameter iterations

In comparison to the normal business state with two measurement parameters adjusted once at a time, the following deductions are outlined:

- The combination of measurement parameters (AB), (AC), (BC) all increase when set at maximum and decrease when set at minimum. From the percentages captured in Table 2, this implies more total processes (TAT) are completed when the combined measurement parameters are set at maximum.
- The combination of (AC) measurement parameters facilitates significant total processes (TAT) completed at (2.40%), followed closely by (AB) at (1.45%), and then (BC) at (0.99%).

Experiment 3

The effects of the three factors are considered together in the three combinations. This experiment adjusted three parameters set to maximum or minimum. The results are summarised in Table 3. Compared to the normal business condition with three measurement parameters adjusted once, the combination of the ABC measurement parameters increases the total number of completed processes (TAT) by **2.35%** when set to the highest and decreases it by **(-3.08%)** when set to the lowest.

Table 3. Tripple combinations

Double	**Max**	**Normal**	**Min**
ABC	**2263 (2.35%)**	2211	**2143 (-3.08%)**

TAT is used as a specific output parameter with scenario experimental examples, as shown, to evaluate the robustness of the integrated framework. Experiments one and two are combined in percentages to quantify how each factor affects the whole model. The quantifiable result, using the TAT as an example in this article, shows that the maximum average time for the flow of the process (A) has a quantifiable impact greater than the efficiency of the process (C). Also, the efficiency of the process (C) has a more significant impact than the maximum throughput of the process (B). A similar replicable scenario could be carried out for larger-scale mining with quantifiable results, such as increased or decreased costs, emissions, water consumption, carbon footprint, etc.

The experimental framework presents a simulated integrated decision-making structure. Based on a scenario impact assessment using key impact parameters of LCA and RCM, with TAT as the quantifiable outcome. The results of the simulation show that it is possible to capture and simulate a combination of LCA and RCM business processes and to quantify the impact parameters of LCA and RCM based on these business processes.

Key deductions

The decision-making framework presented in this article provides useful insights that highlight the need for LCA and RCM stakeholders in the mining sector to maintain and improve operational protocols so they can better understand the business impacts and make more sustainable decisions. Business process competencies need to be improved through BPM strategies that use digital tools and facilitate sustainability measures. The main conclusions are highlighted by a more detailed description of how the investigation addressed the research questions.

RQ1: The bibliometric analysis showed that LCA and RCM complement each other, and revealed several studies that have tried to integrate both approaches to assess business impacts more comprehensively and to make more sustainable decisions. The main lesson of the analysis is highlighting the need for more research into the intelligent use of data-integration tools, which also support both quantitative and qualitative assessment methods and improve decision-making.

RQ2: The document analysis section of the results presents an analysis of documents to provide information on how the case study mining industry compares with global maintenance practices so that more sustainable decisions can be made.

RQ3: The integrated decision-making framework developed shows that BPM has a significant impact on sustainable decision-making. BPM provides an opportunity to operationalize the context of this article and integrate data-driven sustainability decisions into business processes. Using the capabilities of BPM, the authors described how data from different sources are integrated to answer specific research questions. The authors combined the business processes of LCI and FMECA to provide a case study for the proposed development of this article. The reviewed literature confirms that time resources, cost considerations, and data integration require a link between the LCA and the RCM business processes.

RQ4: Simulation, a digital tool used in a variety of fields, facilitates computer models that mimic real-world processes or systems, enabling analysis, testing, and optimization in a virtual environment. This article used a simulation tool, namely Anylogic Software, to pilot the application of the data-integration decision-support framework in practice and its relevance for sustainability. An overview of simulation development, testing, and analysis is presented.

RQ5: The experimental framework presented a simulated integrated decision-making structure. Based on a scenario impact assessment using key impact parameters of LCA and RCM, with TAT as the quantifiable outcome. The results of the simulation showed that it is possible to capture and simulate a combination of LCA and RCM business processes and to quantify the impact parameters of LCA and RCM based on these business processes.

RQ6: Simulation essentially uses digital protocols to replicate real-world operations and provide a digital perspective of the underlying operations. Simulation frameworks can and often do replicate the real world, particularly when used for training or testing purposes. Although simulations are not always perfect, they can provide valuable insights and prepare companies or systems for real-world scenarios. The simulation framework can significantly influence sustainability efforts. By allowing different scenarios to be tested and evaluated, it helps to identify the most effective and efficient strategies to improve business outcomes and resource management.

Implications for theory

- This article underlines that the capacity of BPM will improve the sustainability of LCA and RCM and the decision-making process in the mining industry. BPM offers the opportunity to operationalize and integrate data-driven sustainability decisions in the business processes of the mining industries.
- Using digital tools with simulation as a case study in this article facilitates the development of new sustainability risk assessment standards, such as systematic data collection, that help to identify the most effective and efficient strategies to improve business outcomes and resource management in the mining industries.
- Complements qualitative evaluations provided in current studies that have tried to integrate both LCA and RCM approaches with a potential quantitative rationale to assess business impacts more comprehensively and to make more sustainable decisions. Managers in the mining and manufacturing sectors may review current operationalization protocols to strengthen the integration capabilities of their processes and comprehend or control sustainability risks.

Practical implications

Extension of the scope of LCA and RCM by supplementing existing literature on quantitative modelling research and moving away from qualitative discussions. The results demonstrate the ability to replicate a decision-making model integrating the LCA and RCM business processes for the assessment of the scenario impacts, which makes it easier to make more sustainable decisions. Managers of mining operations may review relevant practical information from the results of this article to consider possible alternatives and to take action based on their current business process operational guidelines.

Originality/value

Future developments in LCA and RCM techniques for business implementations in the mining sector will add value to the uniqueness of this article. Mining stakeholders will gain a better understanding of the importance of integrating LCA and RCM-based business processes to assess business impacts more comprehensively and to make more sustainable decisions. The developed cluster will allow for new areas of current and future research interest.

CONCLUSION

The integration of LCA and RCM based on BPM capabilities is identified as a significant research area. This article's high-level interventions to the body of knowledge are highlighted as follows.

(i) The analysis reviews and compares the results with previous integrations of the LCA and the RCM. The outcomes further demonstrate the feasibility of creating an integrated decision-making framework for LCA and RCM business processes based on BPM capabilities, and the replicable possibility of the decision-support framework in the real world, together with its relevance to sustainability.

(ii) Discuss the significance of business processes and quantifiable parameters in discussions related to the integration of LCA and RCM. A summarized list of LCA and RCM business processes together with measurement parameters that allow for quantifiable evaluations with TAT as the quantifiable outcome is also provided.

(iii) The results of the simulation give guidance to LCA and RCM stakeholders in the mining sector that there is a possibility to capture and simulate a combination of LCA and RCM business processes and to quantify the impact parameters of LCA and RCM based on these business processes.

(iv) Demonstrates how crucial it is to incorporate digital technologies and confirms the need for more research into digital tools for data integration. This provides future research direction on developing fields of LCA and RCM research.

(v) The analysis provides information on how the case study mining industry is performing against global maintenance practices to make more sustainable decisions. The document review supported by the FMECA complements the evaluations provided in this article with qualitative information on the process of operationalization of the proposed integrated framework. FMECA provides data on possible failure modes, their effects, and the criticality of each component. This analysis enables active risk mitigation leading to improved reliability, safety, and operational efficiency in the mining environment.

LIMITATIONS AND FURTHER RESEARCH

The authors acknowledge that developing an integrated digital data approach might be more time-consuming or complex than traditional methods. However, its value cannot be overemphasized enough. Despite certain challenges and limitations based on research, the interventions provided assist LCA and RCM specialists, especially those in the mining sector, in making well-informed decisions. In this article, a case study with TAT as the quantifiable outcome is presented based on defined LCA and RCM input parameters. A few of these articles' shortcomings with potential future research perspectives are noted.

(i) This article was specifically focused on the mining sector. Extending the scope of LCA and RCM to include a more comprehensive context that goes beyond constraints specific to a given industry is important. Future work can investigate how the developments presented can be replicable in other business sectors. With additional efforts expanding on how prior integrations compare based on industrial sectors.

(ii) A case study with TAT as the only quantifiable outcome is presented to assess the robustness of the integrated framework based on defined LCA and RCM input parameters that include business processes. Future investigations may explore digital tools for systematic data collection and integration with more LCA and RCM quantifiable measurement parameters and outcomes. For example, economic constraints, implementation barriers, technical expertise, trade-offs, and stakeholder engagement strategies to translate theory into practice.

(iii) Issues related to data privacy, power dynamics, ethical considerations, and the potential for biased interpretations are issues faced by the authors in the mining company investigated. However, simulation essentially uses digital protocols to replicate real-world operations and provide a digital perspective of the underlying operations. Future outcomes may look at demonstrating the simulated framework with real-world industry-based scenario data.

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