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Adoption of Data-Driven Automation Techniques to Create Smart Key Performance Indicators for Business Optimization

Michael Sishi and Arnesh Telukdarie *

Johannesburg Business School, University of Johannesburg, Johannesburg 2006, South Africa; mike.sishi@gmail.com
* Correspondence: arnesht@uj.ac.za

Abstract: Key performance indicators (KPIs) are crucial for managing business performance and optimization strategies. However, traditional KPIs are inflexible and cannot adapt to changes in staff, business units, functions, and processes. To address this issue, this paper proposes a method that combines statistics, machine learning (ML), and artificial intelligence (AI) to augment traditional KPIs with the flexibility of data-driven automation (DDA) techniques. This study builds a model that takes traditional KPIs generated by an integrated ecosystem as input data and assesses the suitability and correlation of the data using statistical techniques, such as Bartlett's test of sphericity and the Kaiser–Meyer–Olkin (KMO) test of sampling adequacy. The model then employs exploratory Factor Analysis (FA) techniques to identify correlations and patterns, prioritize KPIs, and automatically generate smart KPIs for business optimization. The model is designed to adapt automatically by creating new KPIs as the business evolves and data change. A case study evaluation validates this approach, showing that DDA techniques can effectively create smart KPIs for business optimization. This approach provides a flexible and adaptable way to manage business performance and optimization strategies, enabling organizations to stay ahead of the competition and achieve their goals.

Keywords: process-driven automation; data-driven automation; machine learning; artificial intelligence; business optimization

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1. Introduction

The rapid advancement of technology has led to unprecedented business growth through mergers and acquisitions (Mohammadi et al., 2018) [1]. This growth necessitates the development of effective optimization techniques to ensure success and sustainability [2,3]. This makes optimization a key driver for business success and sustainability strategies [2,3]. Challenges such as the lack of real-time information, absence of value chain optimization, shortage of integrated systems, ineffective communication from decision-makers to individual workers, and isolated pockets of information prompt the need for business optimization [4].

Organizations create a plan to achieve their objectives guided by their business strategy. The success of these objectives relies on defining clear business objectives, which are translated into key success factors using key performance indicators (KPIs) which can be calculated at different business levels, including operational, tactical, and strategic ones. Well-formulated and visualized KPIs have been shown to encourage productive business engagements and continuous improvement. However, traditional KPIs are designed using process-driven automation techniques that rely on strict rules, instructions, procedures, computations, and configurations set by industry experts and stakeholders. This approach makes KPIs inflexible, passive, and unintelligent, as they cannot adjust to changes in the business environment and cannot proactively manage performance.

Therefore, this research is aimed at inventing a model to supplement traditional KPIs by looking at business data, identifying relationships and trends, and creating new smart KPIs (SKPIs) that dynamically adjust themselves as business evolves and data change. To achieve this, this study uses a data-driven automation model that leverages cross-functional KPIs (CFKPIs) generated within an integrated ecosystem. The CFKPIs are then validated for correlation and suitability using machine learning (ML) techniques, namely, Bartlett's test of sphericity and the Kaiser–Meyer–Olkin (KMO) test of sampling adequacy. This study further uses ML to implement decision engines and predictive analytics. In addition, artificial intelligence (AI) techniques of exploratory Factor Analysis (FA) were employed to identify data patterns, correlations, and significance levels of CFKPIs. This, in turn, helped to create SKPIs tailored for business optimization. To achieve this, the following research objectives were formulated:

The first objective was to create a ground-breaking model that serves as a complementary tool to traditional KPIs.

The second objective was to develop and implement mechanisms within the model that enable SKPIs to dynamically recalibrate in response to shifting business dynamics.

The third objective was to evaluate the practical application and effectiveness of the data-driven (DDA) model.

This study holds great importance in advancing the field of business optimization by introducing a new approach to KPIs. By achieving the aims and objectives of this study, the dynamic and adaptive nature of SKPIs contributes to the creation of more resilient and responsive business strategies. This ensures competitiveness and sustainability in an ever-evolving business landscape.

The remainder of this article is structured as follows: Section 2 provides an overview of related studies on automation categories and techniques, key performance indicators, and business optimization. Section 3 introduces the methodology that utilizes statistics, ML and AI techniques, to devise an innovative model that produces intelligent KPIs for business optimization. Section 4 presents the research results, where the effectiveness of the model is evaluated through a case study. Section 5 discusses the research results, and Section 6 concludes this study with implications, recommendations, and potential areas for future research.

2. Related Literature

Optimization is a vital and indispensable process in the business realm, as it meticulously examines and enhances productivity, efficiency, and overall performance, as emphasized by Chang et al. [2] and Rondini et al. [3]. This process plays a pivotal role in ensuring the long-term sustainability and viability of businesses, exerting its influence across a broad spectrum of operational domains, including Finance; Human Resources; Information and Communications Technology; Customer Service; Maintenance; Production; Logistics, Sales, and Marketing; Product and Service Development; Research and Development; Health and Safety; and Integrated Planning, as noted by Telukdarie et al. [4] and Hu and Feng [5].

Given the paramount importance of optimization in driving business success, this literature review undertakes an in-depth examination of the multifaceted dimensions of business optimization. This review encompasses a comprehensive analysis of business optimization, business strategies, key performance indicators, and automation techniques, with the goal of providing a nuanced understanding of the complex interplay between these critical components. By exploring the intricacies of business optimization, this review aims to contribute to the existing body of knowledge, providing valuable insights for businesses seeking to optimize their operations and achieve sustainable success.

2.1. Business Optimization

The process of business optimization entails a detailed analysis and improvement of a business's productivity, efficiency, and performance. This is crucial for ensuring the long-term sustainability and viability of the business, as it enables the organization to operate effectively and adapt to changing market conditions over time. Business optimization can be applied to various facets of an organization, as mentioned in the introduction of this section.

Numerous studies have explored the application of various methods to business optimization. For instance, Yang et al. [6] employed the Bat algorithm (BA) to solve complex engineering design and business optimization problems. In contrast, Mobin et al. [7] utilized evolutionary algorithms (EAs) to address engineering and business optimization challenges. Dominy et al. [8] applied geometallurgy techniques to establish three-dimensional (3D) models that enable the optimization of net present values (NPVs) and effective orebody management in the mining sector.

Wang and Cao [9] developed an implicit rule-based recommendation algorithm (IR-RMINER) to reveal complex and implicit relationships between transactions and to increase the reliability of study recommendations. Smith et al. (2014) [10] applied a mixed-integer program (MIP) solution to create a life-of-business optimization system (LOBOS) that optimizes production scheduling and the granularity of production volumes at a large copper mining complex.

Himeur et al. (2022) [11] applied ML and AI big data analytics to enhance building automation and management systems (BAMSs). By applying supervised and unsupervised one-class support vector machine (OCSVM) ML algorithms, their study successfully detected energy anomalies in residential and office buildings and optimized energy performance in sports facilities, addressing key challenges in BAMS.

Krishna (2023) [12] conducted an in-depth examination of the transformative effects of ML and AI on supply chain transportation, drawing on the existing literature and case studies. This research revealed that the strategic application of predictive analytics, route optimization algorithms, and real-time decision-making enables AI and ML to drive significant improvements in logistics, including enhanced optimization, cost savings, and agility, ultimately leading to more efficient and effective supply chain operations.

James et al. [13] developed a system that leverages big data and ML to optimize business intelligence. Using the k-means clustering algorithm, the system analysed a sample report from the Nigerian National Petroleum Corporation (NNPC) and generated predictive outputs to guide managerial decisions. Their study also explored the application of deep learning algorithms for time-series data analysis, demonstrating the potential for improved results using stacked neural network layers.

Yuen et al. [14] proposed a metaheuristic-based framework to solve the comprehensive index tracking problem (IPT). This framework considers various constraints and optimizes tracking errors and excess returns. Simulation studies demonstrated competitive results using a genetic algorithm, particle swarm optimization, a competitive swarm optimizer, and differential evolution. This framework can incorporate additional practical constraints and has potential for future applications with various metaheuristics and datasets.

Redchuk and Mateo [15] studied ML and AI adoption in the steel manufacturing industry to optimize processes. Their study showcased the potential of new AI-/ML-based business models in traditional industries. The results demonstrate that a No-Code/Low-

Code solution outperformed conventional analytic approaches, highlighting the potential for AI/ML democratization in traditional industries.

These studies demonstrate the extensive use of ML and AI methods to drive business optimization and improve organizational performance. Bharadiya [16] asserts that ML algorithms facilitate the automation of data analysis tasks, including data cleansing, feature extraction, and transformation using statistical techniques. By streamlining these processes, businesses can accelerate data analysis and minimize manual intervention. Moreover, the integration of ML and AI enables the detection of data anomalies, the revelation of hidden patterns, and the provision of actionable insights for optimizing business processes through underlying statistical techniques. This, in turn, allows organizations to pinpoint areas of inefficiency, enhance operational workflows, and drive overall performance improvements.

2.2. Business Strategy

A business strategy is a high-level plan designed to enable a company to achieve specific business objectives. The ultimate goal of a business strategy is to drive growth, establish a strong competitive advantage, and deliver robust financial performance [17]. The success of a business strategy is paramount, as failure to achieve desired outcomes may necessitate a strategic overhaul or potentially even threaten the company's viability [18].

For a business vision, or generic strategy, to be successful, it must be situated within a comprehensive strategic framework [19]. This framework is underpinned by multiple strategies, each with its own distinct objectives and action plans. These strategies are interconnected, with objectives defined for each strategy supporting and reinforcing the objectives of other strategies [20]. This interdependency fosters a cohesive and aligned strategic approach.

The objectives defined within each strategy are subsequently translated into specific targets, which are then pursued through the implementation of lower-level strategies. To ensure the success of a business strategy, it is essential to measure and manage the performance of strategic objectives. This critical aspect of strategic management is discussed in the subsequent section, where the focus shifts to the performance measurement and management of strategic objectives.

2.3. Key Performance Indicators

An effective business strategy implementation relies heavily on the establishment of clear objectives, which are meticulously monitored and refined through the utilization of key performance indicators (KPIs). KPIs serve as detailed specifications that facilitate the tracking of business objectives, providing a tangible measure of success and progress towards organizational goals [21–23]. To ensure the successful implementation of KPIs, it is essential that an organization's vision and strategy are clearly defined, communicated, and aligned with the overall objectives. This enables the establishment of meaningful and constructive KPIs that effectively measure performance and drive business success [24]. A well-defined vision and strategy should be translated into expressive KPIs for each organizational level, including top management, middle management, line management, and the shop floor [21].

Visualizing KPIs is crucial, as this facilitates regular performance discussions, cross-functional assessments, and the escalation of critical topics to management meetings [25,26]. This enables organizations to identify areas for improvement, track progress, and make data-driven decisions. Traditionally, KPI definitions are based on predefined rules and calculations tailored to specific business models [22,27].

By adopting a structured approach to KPI development and implementation, organizations can ensure that their business strategies are effectively translated into actionable objectives, ultimately driving success and sustainability. This involves establishing clear and measurable goals, defining relevant KPIs, and regularly reviewing and refining performance metrics to ensure alignment with organizational objectives.

2.4. Automation Categories and Techniques

Automation is achieved through the application of technologies to perform tasks and manage processes with minimal human interaction. The adoption of advanced technologies for automation can enhance user experience and customer satisfaction through the use of software robots across core processes in the organization [28]. Automation has been adopted in such business sectors as manufacturing, mining, insurance, banking and finance, education, real estate, inter alia [29]. The automation process is divided into two categories, viz., process-driven automation (PDA) and data-driven automation (DDA).

PDA uses (a) robotic desktop automation (RDA) to automate manual processes that are performed at a desktop level, such as completing a form or typing a letter and (b) robotic process automation (RPA) to automate manual processes centrally by providing self-service facilities that enable machines and programs to interact with information through their user interfaces in a process-oriented way. These self-service facilities are available around the clock through pre-programmed digital triggers, freeing humans from performing repetitive and mundane tasks [30,31].

DDA employs ML and AI techniques. ML enables predictive analytics and decision engines in different areas of the business, helping leadership in making the right decisions at the right time for business sustainability and success [32]. Madakam et al. [33] claim that ML yields intelligence aptitude by learning from data with the help of algorithms and subject experts. AI enables deductive and inductive analytics to discover data patterns, correlations, and contextual meaning to data [31]. Goher et al. [32] praise AI for its ability to integrate into human decision-making and to play a vital role in everyday lives through technologies such as the Internet of Things (IoT), cloud comping, and macro services. Upadhya et al. [31] claim that AI is one of the cutting-edge technologies that is utilized to automate business operations, processes, and services.

2.5. Summary of Related Literature

A thorough examination of existing studies reveals that business optimization is a multifaceted and intricate topic, encompassing a broad range of statistical, ML, and AI methods and strategic approaches. Researchers have employed these methods and approaches to address complex engineering and business optimization challenges.

The success of an organization is heavily dependent on its strategic framework, which comprises multiple interconnected strategies that collectively drive business outcomes. The relationships between these strategies are critical, and KPIs play a vital role in monitoring and improving business objectives. A clear and well-defined vision and strategy are essential prerequisites for achieving success, as they provide a roadmap for organizational decision-making and actions.

In addition, automation technologies, including robotic desktop automation, robotic process automation, machine learning, and artificial intelligence, can be leveraged to enhance business optimization. These technologies can be applied using either process-driven or data-driven approaches, each offering distinct benefits and advantages. By understanding and effectively utilizing these various facets of business optimization, organizations can develop and refine their strategic frameworks, ultimately leading to improved overall performance and sustained competitiveness.

3. Research Methodology

This research aims to supplement traditional methods of defining KPIs by integrating DDA techniques for business optimization and sustainability. The focus is on analysing business data generated by systems integrated through PDA to identify patterns, correlations, and trends within the data. This will enable the creation of SKPIs that can adjust dynamically to changing business conditions. The methodology depicted in Figure 1 encompasses two segments. The first segment involves the development of the DDA model through a four-step process of performing data sourcing; data sampling; ML (data validation, decision engines, and predictive analytics); and AI (patterns and correlations, KPI significance, and SKPIs). The second segment involves evaluating the developed model using case study methods, considering the complexities of an ecosystem that generates substantial amounts of performance-relevant data.

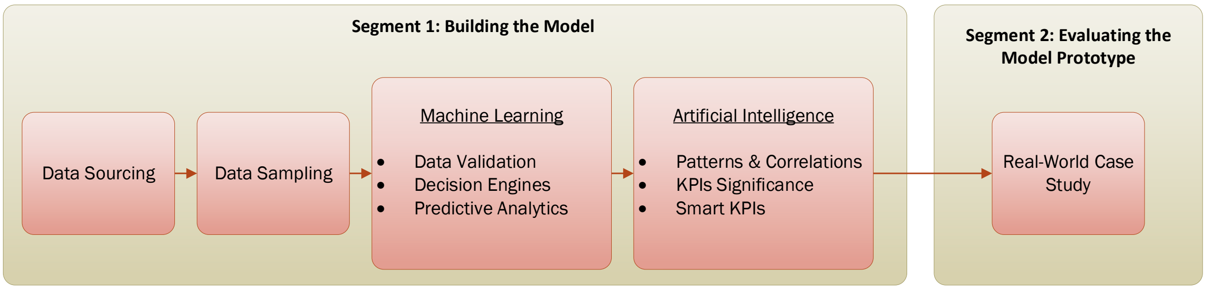

Figure 1. Research process.

In addition to the studies reviewed in Section 2.1, Hao et al. [29] used a data-driven method to diagnose multiplicative key performance degradation in automation processes. This method was aimed at identifying low-level components that increase the variability of process variables and consequently cause degradation in performance. Gao et al. [34] applied data-driven metadata inference to learn from building automation systems (BASs) to reduce energy consumption in residential and commercial building stocks in the US. Upadhya et al. [31] used ML and AI to achieve automation and a data-driven design of polymer therapeutics. Their research was meant for gene delivery, drug delivery, bioactive polymers, drug design, antimicrobial polymers, and organic synthesis.

These studies extracted data produced by process-driven systems in various industries and applied data-driven methods to achieve further automation and to draw engineering insights. These studies extensively employed various techniques, including advanced statistics, ML, and AI, to realize data-driven models. This validates the effectiveness of data-driven methods in supplementing process-driven systems by achieving further automation, extracting and interpreting meaningful patterns and trends from data. Therefore, this study borrows some of the data-driven techniques exhibited by the respective studies to create a data-driven model for smart KPIs to optimize and sustain businesses.

This research is buttressed by an integrated ecosystem that leverages the transformative power of the 4IR integrations, specifically, vertical, end-to-end, and horizontal integrations, through the lens of PDA. Building on the foundational work from previous studies [35–38], this study adopts a comprehensive framework that defines and operationalizes these three 4IR integrations.

The vertical integration, a critical component of this framework, enables real-time connectivity between physical machinery on the shop floor and sensors, control systems, manufacturing systems, and Enterprise Resource Planning (ERP) systems. This networked manufacturing system facilitates seamless communication and information flow between different sections and processes, ensuring that data flow effortlessly from the shop floor to the top floor (ERP) and back. This integration enables organizations to respond rapidly to changing market conditions, optimize production processes, and improve overall efficiency.

End-to-end digital integration, another vital component of this framework, enables organizations to track products throughout their entire lifecycle, from inception and design, manufacturing and distribution, usage by customers, and eventual end of life. This integration facilitates real-time monitoring and management of products, ensuring optimal performance and efficiency. By leveraging end-to-end digital integration, organizations can improve product quality, reduce waste, and enhance customer satisfaction.

Horizontal integration, the third pillar of this framework, fosters digital collaboration between suppliers, organizations, branches, third-party companies, and customers. This integration is achieved by converging ICT systems, processes, and data flows across these business partners, resulting in a fully integrated supply chain. By leveraging horizontal integration, organizations can improve supply chain efficiency, reduce costs, and enhance collaboration with stakeholders.

Figure 2 depicts the integrated ecosystem that underpins this study, illustrating the interconnectedness of these three 4IR integrations and their role in realizing PDA. This ecosystem serves as a foundation for exploring the complex relationships between PDA, 4IR integrations, and business performance and for developing strategies that leverage these integrations to drive business success.

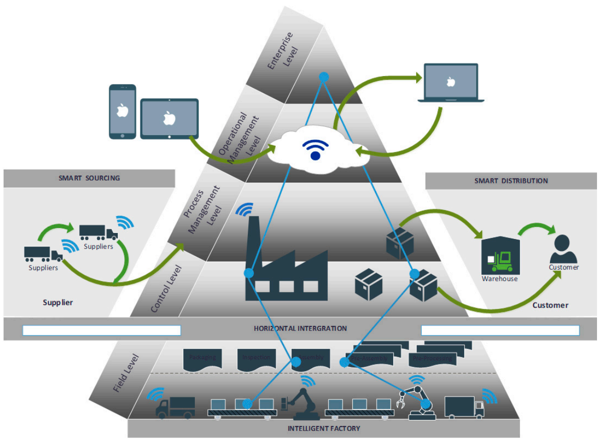

Figure 2. 4IR integrated ecosystem through PDA.

The DDA model was rigorously evaluated through a real-world case study, which was implemented in a company that had successfully achieved a 4IR integrated ecosystem through PDA. As noted by Margherita and Braccini [39], an integrated ecosystem typically generates vast amounts of data. Therefore, it was crucial for the research team to collect and analyse data that aligned with this study's objectives: the adoption of data-driven automation techniques to supplement traditional methods of defining KPIs for business optimization and sustainability.

The existing literature reveals that a typical integrated ecosystem comprises various enterprise functions, each encompassing multiple business functions that utilize diverse processes. These processes, in turn, consist of multiple process steps, each employing one or more resources. The performance of these ecosystem constituents is measured through KPIs, which provide valuable insights into the ecosystem's overall efficiency and effectiveness [40].

To evaluate the DDA model, the research team observed, extracted, and sampled data generated by the KPIs that measured the performance of the process-driven ecosystem's constituents. This data-driven approach enabled the team to assess the efficacy of the DDA model in optimizing business processes and improving overall performance.

To ensure the accuracy, reliability, and integrity of the data, a rigorous and systematic analysis was conducted using a range of advanced ML techniques. These techniques were employed to validate the data, identify patterns and trends, and provide actionable insights that could inform business strategies and could drive organizational success.

ML's statistical techniques played a critical role in facilitating the development of decision engines, which enabled informed decision-making and supported strategic planning. Additionally, predictive analytics capabilities were established, allowing for the forecasting of future trends and outcomes. By leveraging these statistical techniques, this research aimed to provide a comprehensive understanding of the data, identify areas of improvement, and drive business growth.

To uncover hidden insights and relationships within the data, AI exploratory Factor Analysis (FA) techniques were employed. These techniques facilitated the discovery of complex data patterns and correlations, enabling the identification of KPIs that have a significant impact on performance management. Furthermore, the analysis allowed for the automatic creation of SKPIs, which provide a more nuanced and dynamic understanding of business performance. Figure 3 depicts the high-level algorithm of the SKPI model.

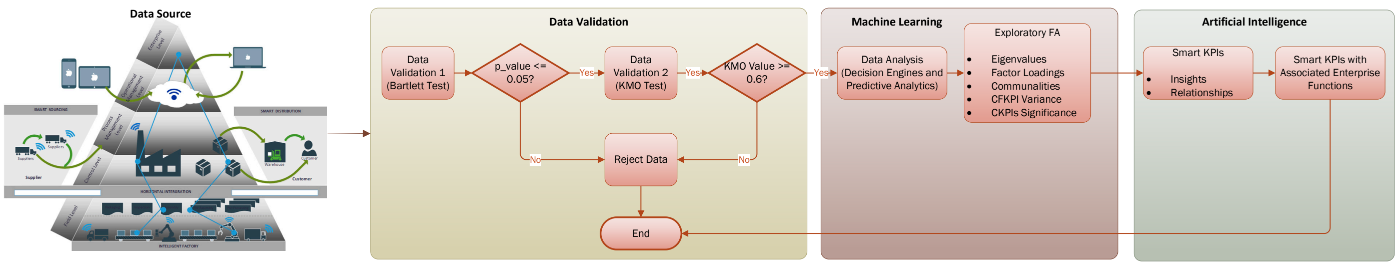

Figure 3. High-level algorithm of the model.

By leveraging these exploratory FA techniques, this research aimed to provide a deeper understanding of the relationships between KPIs and business performance, ultimately informing data-driven decision-making and strategic planning. This study's findings have important implications for organizations seeking to optimize their performance management systems, drive business growth, and maintain a competitive edge in today's fast-paced and data-driven business environment.

3.1. Data Sourcing and Sampling

Data sourcing and sampling is a pivotal process, as the validity of the model outcomes depends on the dataset provided to the model. Illustrated in Figure 4, the process of data sourcing and sampling commenced with the identification and review of journal articles and reports from companies with published inventories of KPIs from respective ecosystems. Subsequently, companies that produced real-world KPI data were identified and requested to make data available where possible. These data were statistically analysed to select only correlated data. Subsequently, a scientific method was applied to create more correlated data that would be sufficient to develop the model.

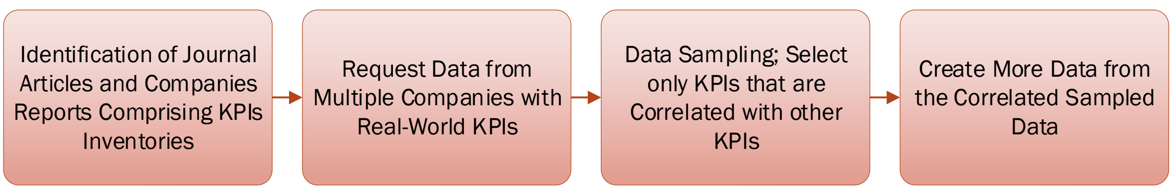

Figure 4. Process for data sourcing and sampling.

Data sampling involved determining and selecting only KPIs that were correlated with other KPIs in the whole dataset. This was achieved by calculating correlation coefficients of the KPIs through Equation (1). KPIs that had negative (<0) or positive (>0) correlations with other KPIs were selected, while those KPIs with correlation values of zero (0) were not selected, as they indicated that they were not correlated with other KPIs in the whole dataset.

$$c = \frac{\mathrm{cov}\left(kpi_i, kpi_j\right)}{\sigma_{kpi_i}\sigma_{kpi_j}} \tag{1}$$

where c is the correlation coefficient, $\mathrm{cov}\left(kpi_i, kpi_j\right)$ is the covariance of ith and jth KPIs, σ_{kpi_i} is the standard deviation of the ith KPI, and σ_{kpi_j} is the standard deviation of the jth KPI.

Subsequent to successful data sampling, a scientific method was applied to create more data (correlated random KPI values) from the correlated data sample through Equation (2). Creating correlated random KPI values ensured that there are adequate data to build the model.

$$x(kpi_i) = random(\leq (kpi_i), \geq (kpi_i), \overline{kpi_i}, \sigma(kpi_i)) \tag{2}$$

where $x(kpi_i)$ is the expected random value for the ith KPI, $\leq (kpi_i)$ is the minimum value of the ith KPI, $\geq (kpi_i)$ is the maximum value of the ith KPI, kpi_i is the value of the ith KPI in the distribution, $\overline{kpi_i}$ is the mean of the ith KPI, and $\sigma(kpi_i)$ is the standard deviation of the ith KPI. The final KPI dataset needed to be validated for its statistical suitability and adequacy to build the model, as discussed in the next section.

3.2. Machine Learning

3.2.1. Data Validation

Data sampling ensured that only KPIs that exhibited correlations with other KPIs in the whole dataset were selected. The sampled data were used to create additional correlated data for the KPIs, resulting in more data to build the model. However, not all KPIs were guaranteed to be sufficiently correlated with other KPIs in the dataset to build the model. Therefore, data validation was performed to ensure that there are enough correlations between the KPIs and that the KPI dataset was suitable for the application of exploratory FA techniques. Data validation was performed through Bartlett's test of sphericity and the KMO test of sampling adequacy techniques, as discussed in the following subsections.

Bartlett's Test

Bartlett's test of sphericity calculates a p-value to verify if the observed variables correlate. If Bartlett's test produces a p-value of 0, this means that the variables in the dataset are correlated and statistically significant; else, the variables are not correlated and are statistically insignificant [41]. In a study that psychometrically evaluated the disease-related fear scale (D-RFS) in adults with epilepsy, Shamsalinia et al. [42] successfully applied Bartlett's test in order to corroborate correlations between data items of 50 epileptic patients. Singh et al. [43] successfully applied Bartlett's test to confirm correlations between 300 potential enablers of the effective implementation of environmental Lean Six Sigma (LSS) in Macro, Small, and Medium Enterprises (MSMEs). For the purpose of this study, Bartlett's test was applied on the dataset to confirm correlations between KPIs, as illustrated in Equation (3).

$$p = f(df, t) \tag{3}$$

where df is the degrees of freedom that indicates the number of independent KPIs whose values have the freedom to vary, t is the test statistic value that indicates if KPIs are correlated, and p (p-value) is the indicator of whether the KPIs are significantly correlated.

KMO Test

The KMO test is applied to verify the suitability of data for the application of exploratory FA techniques by determining the adequacy of each of the observed variables for the complete model. KMO calculates the variance ratio amongst all observed variables. KMO values range between 0 and 1, and a KMO less than 0.60 is deemed unsatisfactory [42]. Balhara et al. [44] successfully applied KMO to measure the sampling adequacy of students' data in a study that developed and validated a brief psychometric scale for gaming disorder and hazardous gaming (GDHG). Rostami et al. [45] successfully applied KMO to test the adequacy of the answers to a 22-item questionnaire from 220 pregnant women in a study that developed a tool for predicting Hepatitis B virus (HBV) infection in pregnant women. For the purpose of this research, the KMO test was applied to determine the adequacy of the KPI dataset to produce SKPIs through exploratory FA techniques based on Equation (4).

$$kmo = \frac{\sum_{j\neq k} r_{jk}^2}{\sum_{j\neq k} r_{jk}^2 + \sum_{j\neq k} u_{jk}^2} \tag{4}$$

where r_{jk}^2 is the correlation matrix between KPIs (from kpi_j to kpi_k) that determines how each KPI is correlated to other KPIs in the same dataset, u_{jk}^2 is the partial covariance matrix that determines the correlation between two KPIs when other KPIs are not considered, kmo is the value that determines the adequacy of the KPI dataset for the application of FA techniques to produce SKPIs.

3.2.2. Decision Engines and Predictive Analytics

Properties of KPIs

Each KPI is embedded within a complex hierarchical framework, comprising multiple interconnected layers. Specifically, each KPI is characterized by a set of attributes, including enterprise function, business function, business process, process step, and resource. To provide a meaningful business context and to facilitate informed decision-making, these properties were systematically assigned to each KPI, as depicted in the hierarchical structure in Figure 5, subsequent to a rigorous validation process.

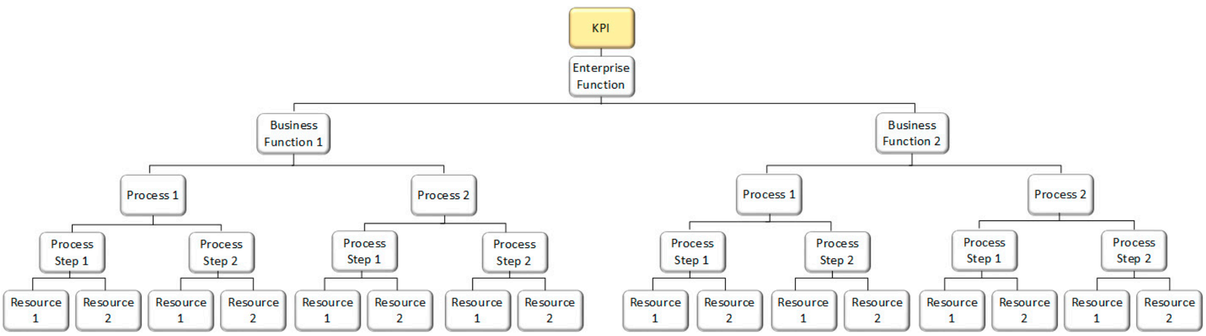

Figure 5. Properties of a KPI.

Assigning properties to KPIs enables the development of decision engines and predictive analytics, allowing performance to be managed from the perspectives of these properties. Moreover, changes in one property can have a ripple effect, influencing other properties, business performance, and KPI values. Identifying these interdependencies enables the recognition of properties that underpin good and bad business performances, ultimately informing optimization decision-making and actions.

Understanding the extent of interdependencies and the influence of these properties on business performance enables predictive analytics. Specifically, the model can leverage this knowledge to predict future business performance by monitoring the behaviour and status of KPI properties. By doing so, organizations can proactively identify areas of improvement, optimize their operations, and drive business success.

3.3. Artifical Intelligence

3.3.1. Data Patterns and Correlations

To uncover underlying patterns and correlations within the KPI data, we employed exploratory analysis techniques. Specifically, we utilized exploratory FA methods, which involve reducing the complexity of multiple correlated variables into a smaller set of unobserved variables, known as factors. These factors are characterized by similar response patterns, enabling the identification of underlying structures within the data [41]. In the context of this study, the application of exploratory FA techniques facilitated the reduction of a large number of KPIs into fewer, more manageable groups. The formation of these groups was determined through the calculation of eigenvalues, as described in Equation (5).

$$\begin{gathered} av = \lambda v \\ av - \lambda v = 0 \\ (a - \lambda i)v = 0 \end{gathered} \tag{5}$$

where a is the matrix of KPIs, v is the vector of KPIs arranged in n rows and n columns, λ is the value of each KPI, and i is the identity matrix with rows of [λ, 0] and [0, λ]. The number of eigenvalues greater than one equals the number of groups of KPIs created by the model. Subsequently, the groups of KPIs were created, and rotated factor loadings were calculated to determine correlation coefficients (strengths) of the observed KPIs to the respective groups based on Equation (6).

$$l = \left[\sqrt{\hat{\lambda}_1 \hat{e}_1}\sqrt{\hat{\lambda}_2 \hat{e}_2} \ldots \sqrt{\hat{\lambda}_i \hat{e}_i}\right] \tag{6}$$

where l is the rotated factor loading, and $\hat{\lambda}_i \hat{e}_i$ is the eigenvalue–eigenvector pairs. Rotated factor loadings were further used to calculate the variance explained by each of the KPIs in every group and the variance explained by each group in the entire dataset.

Creating groups of KPIs decreases data complexity by reducing a large number of KPIs into fewer groups. KPIs in one group are linearly correlated and interdependent on each other but not strongly correlated to and interdependent on KPIs in other groups. This taxonomizing makes it easy to distinguish between KPIs that are significantly correlated and those that are not. A change in one KPI can affect the rest of the KPIs in the same group. This interdependency means that changes in one or more properties of a KPI can affect properties of other KPIs in a group, thus affecting performance positively or negatively. KPI groups enable the effective identification and management of KPIs that strive to achieve common goals. Moreover, these groups can help reveal the common goals shared by the correlated and interdependent KPIs.

3.3.2. Significance Levels of KPIs

Discovering the individual impact of each KPI on performance management is crucial. This knowledge enables organizations to allocate attention and optimization resources effectively, prioritizing the most critical KPIs and their associated properties. FA techniques utilize communalities to quantify the proportion of variance in each observed variable that is explained by underlying common factors [42]. In this study, we leveraged communalities to assess the level of significance of each KPI on performance management. By applying Equation (7), we calculated the variance in each KPI that is accounted for by common groups of KPIs. This approach allowed us to evaluate the individual contribution of each KPI to performance management, providing valuable insights for informed decision-making and optimization strategies.

$$h_i^2 = r_{i1}^2 + r_{i2}^2 + r_{i3}^2 + \ldots + r_{ij}^2 \tag{7}$$

where h_i^2 is the communality of the ith KPI in all groups, and r_{ij}^2 is the proportional variance of the ith KPI in the jth group.

Each KPI is associated, to a certain degree, with all groups of KPIs but cannot have the same degree of association with more than one group. Therefore, it was pivotal to calculate the degree to which each of the KPIs is associated with each group. This was performed by calculating the variance explained by each KPI in the respective groups based on Equation (8). One or more KPIs can dominate a group if they equally explain the biggest variances. Determining the dominance (significance) level of each KPI in a group enables the organization to prioritize or give urgent attention to the most significant KPIs and related properties.

$$r_{ij}^2 = \left(l_{ij}\right)^2 \times 100 \tag{8}$$

where r_{ij}^2 is the proportional variance of the ith KPI in the jth group, and l_{ij} is the factor loading of the ith KPI in the jth group. Each KPI is finally assigned to a group that retains the most variance for that particular KPI, ensuring that a KPI is associated with only one group.

The identified groups of KPIs collectively capture a significant portion of the total variance within the entire dataset. This proportion represents the combined level of significance or contribution that these groups of KPIs have on performance management. Furthermore, each individual group of KPIs explains a distinct proportion of the total variance in the dataset. This proportion indicates the degree of significance or contribution that each group of KPIs has on performance management. Notably, the first group explains the largest proportion of variance, while the last group explains the smallest proportion. Consequently, the group of KPIs that explains the most variance has the greatest impact on performance management, whereas the group explaining the least variance has relatively less impact.

To determine the significance level of each group of KPIs on performance management, we computed eigenvalues using rotated factor loadings. Specifically, we calculated the proportion of total variance explained by each group of KPIs, as illustrated in Equation (9). This approach enabled us to quantify the relative importance of each KPI group in influencing performance management.

$$\hat{\lambda}_j = (g_1 l_1)^2 + (g_1 l_2)^2 + \ldots + (g_1 l_n)^2 \tag{9}$$

where $\hat{\lambda}_j$ is the eigenvalue of the jth KPI group, g_j is the jth KPI group, and l_n is the nth rotated factor loading.

3.3.3. SKPIs

The grouping of KPIs results in the creation of new, previously unknown SKPIs, where each KPI within a group is treated as a variable. As illustrated in Figure 4 of Section 3.2.2, the highest-level property of each variable (KPI) is the enterprise function. Therefore, identifying the dominant enterprise function within each SKPI is crucial. To achieve this, we measured the most dominant variable (i.e., the KPI with the highest variance or rotated factor loading) within each SKPI and determined its associated enterprise function. The enterprise function with the highest dominance becomes the owner of the SKPI, and the SKPI is subsequently named after this dominant enterprise function. In cases where two or more enterprise functions exhibit equal dominance, they share ownership of the SKPI. This study utilized Equation (10) to formulate SKPIs and associate them with their respective dominant enterprise functions, providing a structured approach to SKPI creation and ownership assignment.

$$skpi_{i_{ef}} = f\left(kpi_{1_{ef_j}}, kpi_{2_{ef_j}}, kpi_{3_{ef_j}}, \ldots, kpi_{n_{ef_j}}\right) \quad (10)$$

where ef is the enterprise function, $skpi_{i_{ef}}$ is the ith smart SKPI mapped to the most dominating ef, and $kpi_{n_{ef_j}}$ is the nth variable of the ith SKPI and is associated with the jth ef. An evaluation is pivotal for demonstrating the model's effectiveness to produce SKPIs in order to optimize a business and to yield success and sustainability.

3.4. Prototype Evaluation

This study evaluated the effectiveness of a prototype through a case study. A prototype was used as this can demonstrate the feasibility of a new idea or technology, especially when dealing with innovative concepts or unexplored territories [46] Using a prototype, researchers can test and validate their ideas or concepts before investing significant resources in a full-scale development [47]. This approach was also chosen because it helps to identify potential flaws or areas of improvement early in the process [48]. Hence, this segment discusses the methods and techniques used to evaluate the effectiveness of the prototype.

3.5. Case Study

The prototype was evaluated through a case study and observations to provide a practical and real-world context for evaluation. Case studies were selected because they allow for a detailed examination of the prototype's strengths and weaknesses, enabling researchers to gather nuanced insights that may not be apparent in controlled environments [49]. In addition, case studies facilitate the exploration of intricate interactions that prototypes may exhibit in complex systems, providing a holistic view of the prototype's performance in a dynamic environment. Overall, the use of case studies in a prototype evaluation allows for a realistic and comprehensive evaluation of the prototype's performance in practical scenarios that mimic actual usage conditions [46].

3.6. Summary

This study aims to revolutionize the definition of KPIs by integrating DDA into traditional methodologies. By leveraging DDA to analyse business data, underlying patterns, correlations, and trends can be uncovered, ultimately enabling the creation of dynamic SKPIs. This research employed a four-stage model development approach, encompassing data sourcing, sampling, ML, and AI. The model's efficacy was subsequently evaluated through a real-world case study conducted within a highly integrated ecosystem, characterized by vertical, end-to-end, and horizontal integrations. This study utilized ML to validate data integrity, develop decision engines, and create predictive analytics. AI was employed to identify patterns and correlations, determine KPI significance, and generate SKPIs. Data validation was ensured through Bartlett's test of sphericity and the KMO test of sampling adequacy. Decision engines and predictive analytics were developed using KPI properties, while an exploratory analysis revealed data patterns through FA. The significance of each KPI was measured, leading to the creation of SKPIs associated with dominant enterprise functions. The model's optimization potential was evaluated in a real-world business setting, and the results obtained using this method are presented in the following section.

4. Results

This section comprehensively discusses the evaluation of the model through a real-world case study at a highly integrated ecosystem that encompasses vertical, end-to-end, and horizontal integration layers of 4IR.

4.1. Data-Driven Automation: Case Study

The case study was performed at an open pit uranium mining company. The mine has an integrated ecosystem with six systems, viz., Enterprise Resource Planning (ERP) for managing business functions within a centralized and integrated system, Geology and Mine Planning (GMP) for ensuring the feasibility of profitably extracting minerals from identified resources, a Modular Management System (MMS) for managing mining production and a fleet of equipment in the open pit, a Fuel Management System (FMS) for controlling the fuel supply and consumption, a Tire Management System (TMS) for monitoring and managing the utilization and lifecycle of tires and rims, and a Manufacturing Execution System (MES) for production management in the processing plant where uranium is extracted from ore and is processed into finished products. The participating systems in the vertical integration were ERP, FMS, MMS, TMS, and MES. The end-to-end integration was made of ERP, GMP, MMS, and MES. The horizontal integration consisted of ERP, FMS, MMS, TMS, GMP, and MES.

4.2. Results of Data Sourcing and Sampling

The mine's integrated ecosystem generates CFKPIs by aggregating datapoints from various systems, enterprise functions, and organizational levels. The production of these CFKPIs adheres to strict, predefined definitions, computations, and business rules established by PDA methods. Our research used data-driven automation (DDA), which leverages statistics, ML, and AI to augment traditional, rule-based methods for generating CFKPIs, thereby creating more dynamic and intelligent performance indicators.

To initiate the DDA process, a sample of 100 CFKPIs was selected, focusing on data generated in 2015 and associated with five key enterprise functions: Finance, Logistics, Maintenance, Planning, and Production. This sampling effort yielded a comprehensive dataset consisting of 300,000 datapoints (100 CFKPIs $\times$ 3000 observations each), as illustrated in Table 1. The selection of these CFKPIs was guided by the number of enterprise functions, key performance areas, and available data sources within the mine.

To ensure the representativeness of the KPIs, the research design guaranteed coverage of all systems, key enterprise functions, and organizational levels within the mine. The implementation of data-driven automation was facilitated through the Python programming language, utilizing the Spyder Integrated Development Environment (IDE) and Jupyter Notebook. The subsequent sections provide a detailed discussion of the data-driven automation implementation.

Table 1. CFKPIs elicited from the mine's systems.

Component Changes	Consumption vs. Budget Benchmark	Failure Cost/Operating Hour	Maintenance Ratio (Planned vs. Unplanned Maintenance)
Failure per position	Cost per hour	Failure cost/tonne	Manual tag transactions (hours)
Failures	Cost per ton	Failure cost per operating hour	Material per category (per period)
Pressure measurements	Cost vs. budget	Failure cost per tonne	Mechanical vs. electronic recon
Tyre tread utilization	Cost/value of inventory (fitted vs. unfitted)	Failure type per position	Medium-term plan (tonnes per period)
(Modular vs. FMS)	Crusher feed (total)	Fresh rock vs. cover	Metres drilled
Acid (per period)	Cycle times	Fuel burn rates	MTBF
Average downtime per failure type	Depletion vs. plan	Grade (per period)	MTTR
Average fuel consumption per cycle or round trip	Detailed failure report	Grades	Number of failures per position
Average payload	Dilution per material category (per period)	Holes drilled	OEE
Average repair time per failure type	Direct to crusher vs. stockpile/rehandling	Holes probed	Ore moved (per period)
Avg. tyre life (hours)	Distance covered	Holes sampled	Ore tonnes moved
Blasted inventory	Drill rates	Idle fuel consumption	Payloads below target payload
Blasted reserve available	Drilled reserve	Infill drilling metres	Payloads over target payload
Bowser—receipts vs. issue	Drilled reserve available	Infill metres vs. budget	Powder factor
Broken reserve	Empty fuel consumption	Items in suspense account	Reserve model
Budget vs. actual tyres used	ENGEN—receipts vs. issue	Laden fuel consumption	Rod life
Availability	Failed vs. worn tyre scraps	Litre/tonne.km	Scheduled maintenance adherence
Consumption per hour	Failed vs. worn tyre scraps (%)	Litres per metre	Short-term plan (tonnes per period)
Fuel consumption per ton	Failure cost	Maintenance availability	Stock level (split by valuation class: new, repaired, or twinning)
Stock tank levels	Tonnes per hour	Total tonnes moved	Waste tonnes moved
Survey tonnes vs. modular tonnes	Tonnes per litre	Total tyre cost	Wear/tonne (mm/ton)—only for trucks
Threshold limits exceeded	Top breakdown count per machine	Total tyre cost (NAD/ton)	Wear cost
TKPH	Breakdown per machine	Use of availability	Wear per tonne
Tonnes per drill metre	Total reserve (drill and broken)	Waste (per period)	Wear rate (operating hrs/mm)

4.3. Results of Machine Learning

ML learning was applied in this study to achieve data validation, decision engines, and predictive analytics to help management make the right decisions at the right time to establish competitive advantage, success, and sustainability for this business.

4.3.1. Results of Data Validation

All the CFKPIs sampled in Section 4.2, as shown Table 1, were validated for correlation and suitability for data-driven automation. The Bartlett's test of sphericity was applied on 300 000 datapoints (100 CFKPIs $\times$ 3000 observations each) based on Equation (3) of Section 3.2.1. The results reveal that the dataset of CFKPIs encompassed enough correlations and was statistically significant (t-value: $-936{,}049.849$; p-value: 0.000). Subsequently, the KMO test of sampling adequacy was applied on 300 000 datapoints based on Equation (4) of Section 3.2.1. This test yielded 0.999, indicating the marvellous adequacy of the CFKPI dataset for data-driven automation. Table 2 illustrates the results of validating the CFKPI dataset through Bartlett's test of sphericity and the KMO test of sampling adequacy for the year 2015.

Table 2. Results of data validation.

Bartlett's Test of Sphericity	t-Value (t)	−936,049.849
	Degrees of freedom (df)	99
	Significance (p-value)	0.000
Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy		0.999

4.3.2. Results of Decision Engines and Predictive Analytics

CFKPIs were analysed comprehensively following the successful implementation of data validation techniques. All five hierarchical levels of the properties introduced in Section 3.2.2 were maintained by each CFKPI. Figure 6 illustrates the average fuel consumption per cycle CFKPI incorporated into the five-level properties structure. The average fuel consumption per cycle belongs to the Logistics enterprise function. The Logistics enterprise function encompasses three business functions, viz., Inbound Logistics, Internal Processes, and Outbound Logistics. These business functions encompass multiple processes each. The Internal Processes business function and two fuel-related processes are demonstrated. The Internal Processes business function encompasses, inter alia, such processes as "Store Fuel" and "Measure Fuel Consumption per Cycle". The first process (Store Fuel) encompasses the "Dispense Fuel in the Tank" and "Record Dispensed Fuel" process steps. The first process step uses three resources, viz., "Fuel Tank", "Dispenser Truck", and "Dispenser Truck Driver". The second process step uses two resources, viz., "Operator" and "Industrial Tablet".

The second process (Measure Fuel Consumption per Cycle) encompasses three process steps, viz., "Read and Record Fuel Consumption", "Get and Record Cycle Counts", and "Compute Fuel Consumption per Cycle". The first and second process steps use two resources each, viz., "Operator" and "Industrial Tablet". The third process step uses two resources, viz., "Server" and "Application Software."

This structure facilitated efficient troubleshooting through the 5 WHYs root cause analysis technique adopted from [50]. A practical scenario is investigating a sudden increase in fuel consumption at the mine, as illustrated in Figure 7.

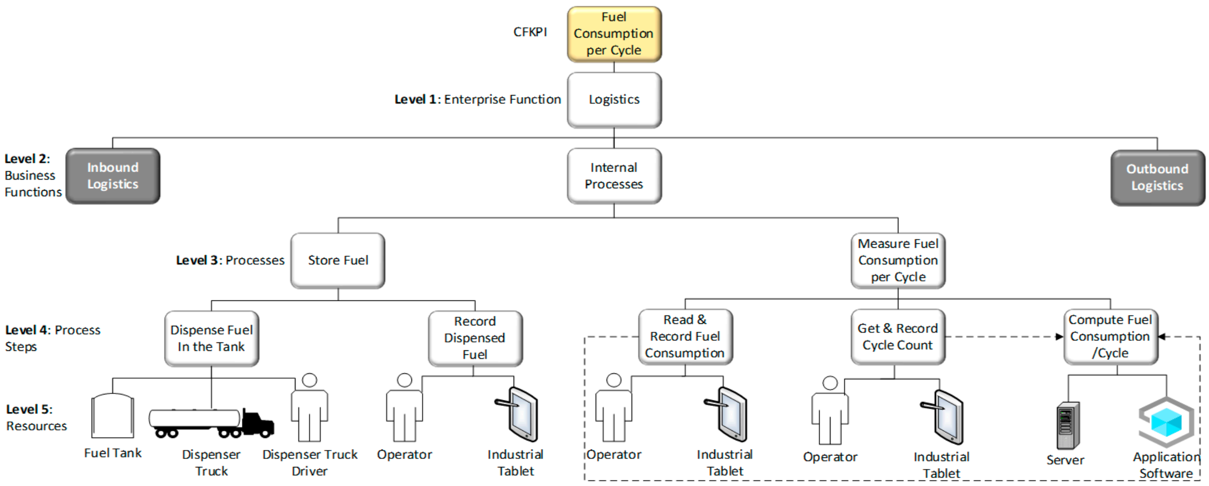

Figure 6. Average fuel consumption per tonne CFKPI.

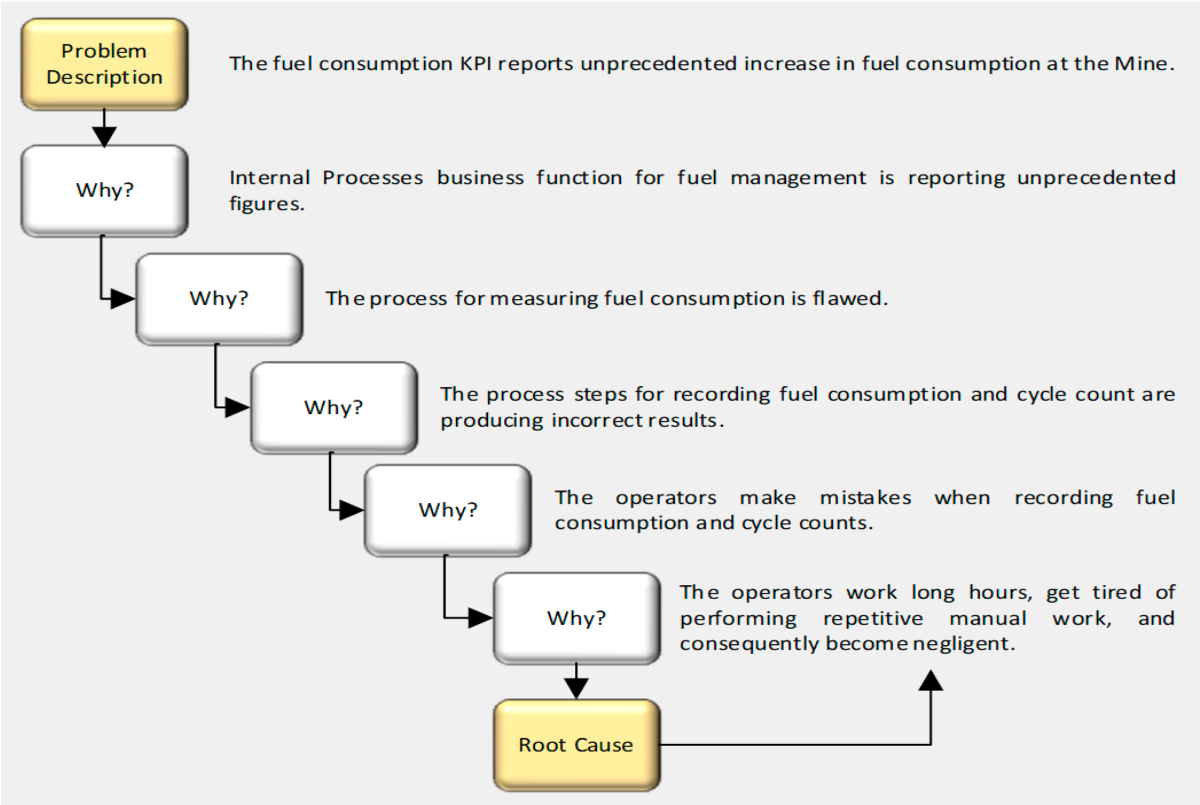

Figure 7. Five WHYs root cause analysis technique for fuel consumption increase.

Discovering the root cause of a sudden increase in fuel consumption resulted in informed optimization decision-making. A project to prevent the inaccurate recording of fuel consumption was initiated by enhancing TMS to automatically read through sensors and record fuel consumption. This enhancement eliminated human intervention and unnecessary resources, sped up recording processes, and provided accurate recordings of fuel consumption. An inaccurate recording of cycle counts was rectified by enhancing MMS with a geographical positioning system that records the round trips of trucks in real-time.

The same 5 WHYs technique discussed above was applied to find the root cause of exceptional performances (i.e., accurate reporting of fuel consumption) indicated by the average fuel consumption per cycle CFKPI. The root cause of exceptional performance was the automation of process steps. That is, automating the recording of fuel consumptions and cycle counts yielded positive results, and the mine consequently invented a strategy for optimizing business through process automation.

Furthermore, discovering the extent to which CFKPI properties influence performance enabled predictive analytics. The average fuel consumption per cycle was predicted by observing the number of cycles made by ore-hauling trucks. Reducing the number of cycles through proper planning (e.g., scheduling of trucks only when there is ore to be hauled and the daily target has not been achieved) reduced the fuel consumption and resulted in significant cost savings over time. The decision engines and predictive analytics were subsequently employed by the mine for all the company KPIs.

There was a possibility that the data patterns for CFKPIs could experience sudden changes or anomalies over time, which could potentially undermine the accuracy and reliability of the model's results. Therefore, we incorporated data visualization to enhance anomaly detection capabilities. By leveraging visual representations of data, domain experts, including business analysts and subject matter experts, gained valuable insights into the business context. This enabled them to provide informed guidance on what constitutes normal behaviour, expected patterns, and typical trends within the data. Consequently, this collaborative approach facilitated a more accurate identification of anomalies and supports data-driven decision-making. Furthermore, we had options to address data anomalies, such as data imputation, interpolation, or error deletion. However, we opted to preserve the raw data to identify and fix underlying issues. This approach was supported by the application of the 5 WHYs root cause analysis to investigate a sudden increase in fuel consumption at the mine. This approach allowed stakeholders to examine the underlying causes of the anomaly, enabling a deeper understanding of the CKPI in question and applying relevant solutions.

The application of ML on CFKPIs enabled deeper insights into business performance. This helped in determining the root causes for good and poor performances, resulting in informed business decisions. Predictive analytics was achieved by observing the properties of each CFKPI and by predicting the future performance outcomes based on the behaviours of these properties.

4.4. Artificial Intelligence

This research adopted an inductive approach to apply an exploratory analysis through FA techniques to complete DDA. The inductive research approach examines collected data, looks for patterns and correlations, and develops theories that could explain patterns and correlations in the data [51].

4.4.1. Results of Data Patterns and Correlations

Exploratory FA techniques were applied on 300,000 datapoints of CFKPIs to develop an inductive research approach. These techniques discovered, through the calculation of eigenvalues based on Equation (5) of Section 3.3.1, eleven groups of CFKPs that shared significant common patterns and correlations. Significant common patterns and correlations were determined by observing eigenvalues greater than one. The calculated eigenvalues were (1) 52.895, (2) 1.5856, (3) 1.495, (4) 1.405, (5) 1.332, (6) 1.269, (7) 1.247, (8) 1.189, (9) 1.153, (10) 1.109, and (11) 1.096. Therefore, eleven groups of CFKPIs were created using the orthogonal rotation method (varimax) in order to produce a rotated factor loading for each CFKPI. The rotated factor loadings were calculated using Equation (6) of Section 3.3.1. CFKPIs in each group were significantly correlated and interdependent on each other. The correlations and interdependencies of CFKPIs in the 1st group are illustrated by the Interrelationship Diagram (ID) in Figure 8. An ID reveals cause-and-effect relationships that are not easily recognizable [52].

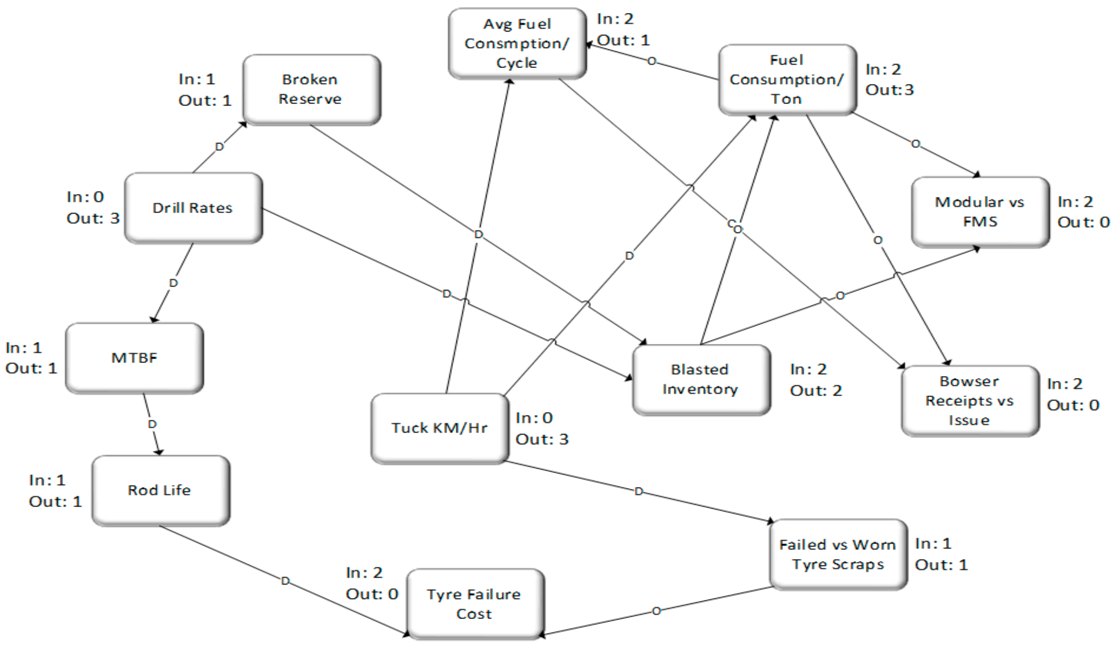

Figure 8. Correlations of CFKPIs in the 1st group.

This ID reveals CFKPIs that were drivers (D) and the ones that were outputs (O). Inputs from the driving CFKPIs are denoted by arrows labelled with a "D", and outputs from output CFKPIs are denoted by arrows labelled with an "O". Each CFKPI can be influenced directly or indirectly by one or more driving or output CFKPIs, and the same CFKPI can be a direct or an indirect driver of other CFKPIs. For example, the truck speed (D) directly drove (influenced) the average fuel consumption per cycle (O) and fuel consumption per tonne hauled (O), thus indirectly driving fuel bowser receipts and issues (O). The average fuel consumption per cycle (O) and fuel consumption per tonne hauled (O) were also direct drivers of the amount of fuel received and issued by the bowser (O). That is, a decrease in fuel consumption reduced the amount of fuel dispensed (issued) from the bowsers and consequently decreased the amount of fuel to be replenished (received) in the bowsers. The increase in fuel consumption resulted in more fuel dispensed from and replenished in the bowsers.

The correlations and interdependencies of CFKPIs in the 1st group revealed by this ID are further clarified by the Causal Loop Diagram (CLD) in Figure 9. A CLD reveals variables that have direct influence on other variables, that is, variables that trigger occurrences of other variables [53].

The success of the mine's cost-saving business strategy was underpinned by, amongst other factors, the ability of the Logistics enterprise function to plan accurately. The ability of the Logistics enterprise function to plan accurately was underpinned by the relationships and interdependencies of the CFKPIs in one or more groups. The drill rates determined the time it took before a drill failed when in operation. The life of the drill rod was determined by the time it took before the rod failed when in operation. The number of broken reserves was determined by the drill rates. Broken reserves determined the available blasted inventory. The blasted inventory resulted in the number of tonnes to be excavated, loaded, and hauled. This resulted in the fuel consumption per tonne hauled. The amount of fuel consumption per tonne hauled was also influenced by the speed of trucks during hauling. The speed of trucks also influenced the rate at which tyres failed or got worn out and the average fuel consumption per cycle. The failed and worn-out tyres had a direct impact on the cost of the tyre failure. The fuel consumption per ton and blasted inventory enabled a comparison between mining production (Modular) and fuel consumption (FMS). The fuel consumption per cycle and fuel consumption pet tonnes hauled enabled a comparison between the bowser receipts and issues. The fuel consumption per tonne hauled directly influenced the average fuel consumption per cycle. The bowser receipts vs. issues and tyre failure costs directly influenced the mine's operational costs. The mine's operational costs reflected the accuracy level (%) of logistical planning. Increasing the level of accuracy in logistical planning became the common goal for the CFKPIs in the 1st group. Consequently, the logistical planners used the CFKPIs and relevant constituents in the 1st group to fine-tune planning. ID techniques were further employed to reveal the relationships and interdependencies of CFKPIs in the 2nd group, as illustrated in Figure 10.

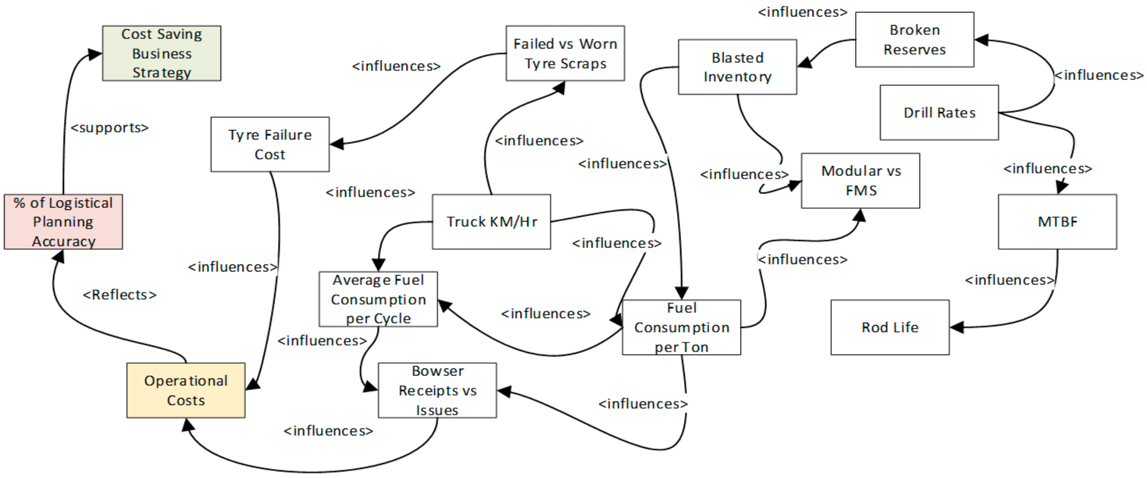

Figure 9. CLD for CFKPIs in the 1st group.

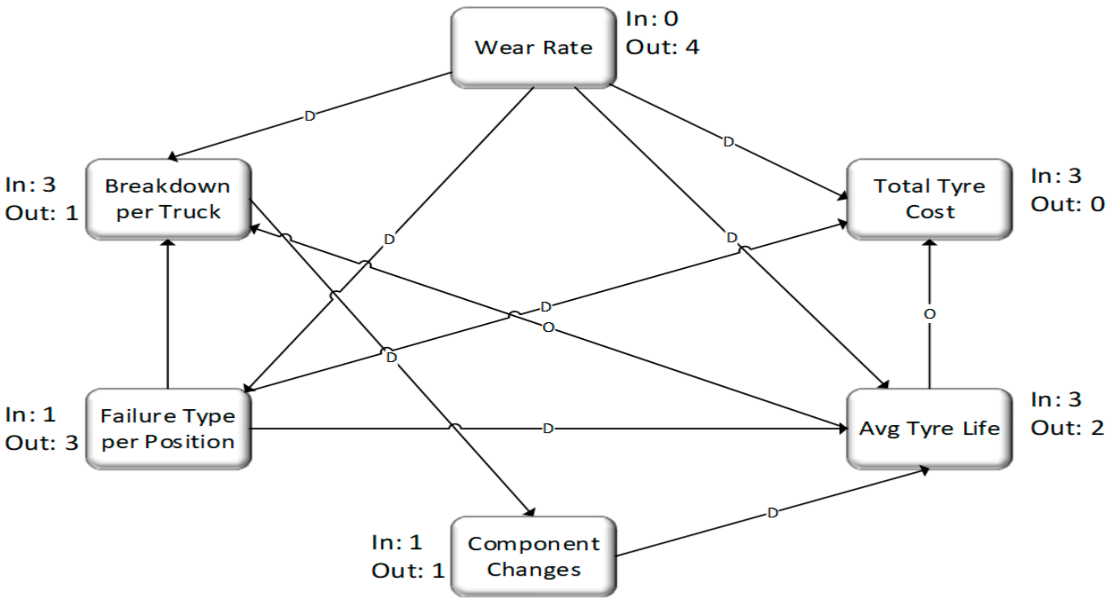

Figure 10. Correlations of CFKPIs in the 2nd group.

The ware rate was the main driver in the 2nd group, as it directly drove the breakdowns per truck, failure type per position, and average tyre life and indirectly drove the total tyre cost and component changes. The relationships and interdependencies of the CFKPIs in the 2nd group are clarified comprehensively by the CLD depicted in Figure 11.

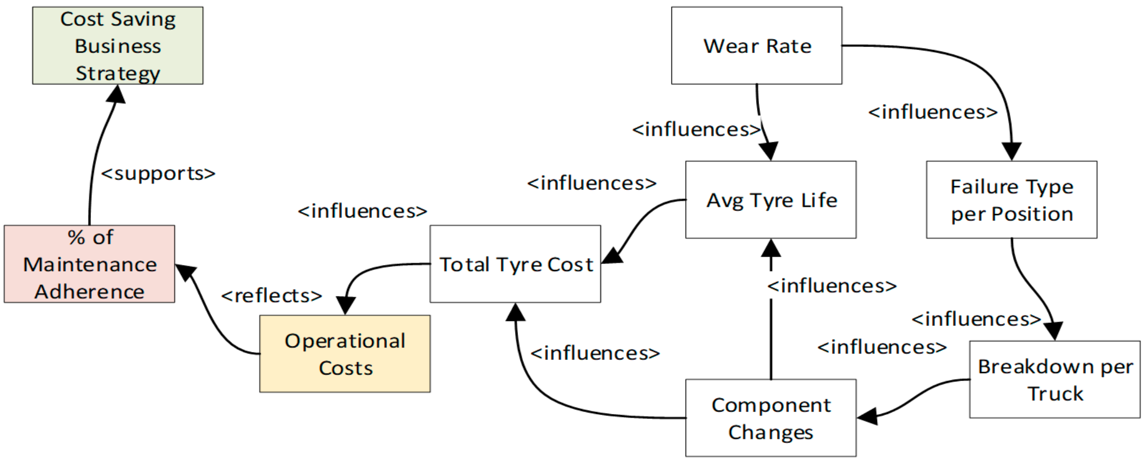

Figure 11. CLD for CFKPIs in the 2nd group.

The 2nd group of CFKPIs contributed to the mine's cost-saving strategy by revealing whether the maintenance plan was adhered to in order to reduce the amount of unplanned downtime, which increased operational costs. The wear rate caused tyre failures in various positions of the trucks (i.e., right–front, left–front, right–rear, left–rear). The wear rate determined the average tyre life, which in turn contributed to the total tyre cost. Tyre failures caused breakdowns that required changes of components. Changes of components affected the average tyre life and contributed to the tyre cost. The tyre cost directly affected the mine's operational costs. The operational costs revealed the level of maintenance adherence achieved by the mine's Maintenance enterprise function. Enhancing the level of maintenance adherence became the common goal for the CFKPIs in the 2nd group. The ID and CLD techniques were applied to all eleven groups to reveal the relationships and interdependencies between CFKPIs that served common goals.

4.4.2. Significance Levels of CFKPIs to Performance Management

Communalities were calculated using Equation (7), introduced in Section 3.3.2, to discover the significance level of each CFKPI on the performance management of the mine's operations. The top ten CFKPIs with highest communalities, illustrated in Figure 12, had the most significant impact on the performance management of the mine's operations. Therefore, optimizing the properties of these CFKPIs guaranteed positive performance results for the mine's operations.

The average fuel consumption per cycle held a maximum of 0.774 of the total communality. This means that the variation in the average fuel consumption per cycle could have had a maximum of a 77.4% impact on the performance management of the mine's operations, followed by ore tonnes moved (0.730), tonnes per drill metre (0.723), scheduled maintenance adherence (0.717), drill rates (0.714), failed vs. worn tyre scraps (0.712), cost vs. budget (0.711), blasted reserve available (0.703), depletion vs. plan (0.701), and modular vs. FMS (0.699).

Each CFKPI was associated, to a certain degree, with all groups of CFKPIs. The proportional variance was calculated, using Equation (7), discussed in Section 3.3.2, to discover the degree to which each CFKPI is associated with each group of CFKPIs. Each CFKPI was assigned to a group that retained the most variance for that particular CFKPI, ensuring that a CFKPI is associated with only one group. Moreover, a cut-off point of 0.4 for factor loadings was applied in order to keep only significant CFKPIs in the respective groups. CFKPIs in the same group were considered to be highly correlated and influential to each other. This means that a change in one of the CFKPIs or its constituents affected the rest of the members in the group. Therefore, managing CFKPIs as groups that strive to achieve respective common goals supplemented the ability to manage these CFKPIs individually.

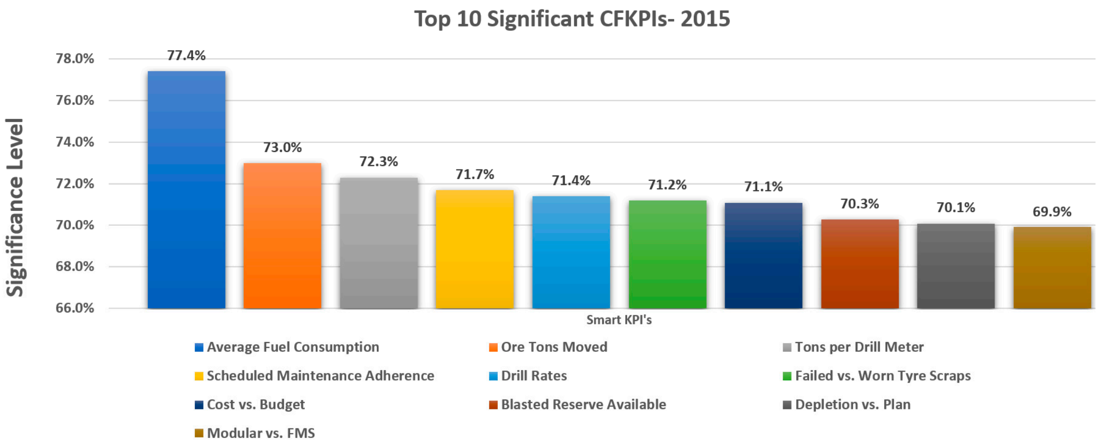

Figure 12. Top 10 significant CFKPIs in 2015.

The groups of CFKPIs collectively explained a proportion of the total variance in the whole dataset. This variance proportion represented the collective level of significance or contribution accounted for by these groups of CFKPIs on the performance management of the mine's operations. The analysis results reveal that the eleven groups of CFKPIs collectively explained 61.637% of the variation in the whole dataset. This means that these groups collectively accounted for 61.637% of the impact on the performance management of the mine's operations. Moreover, each group of CFKPIs explained a proportion of the total variance in the CFKPI dataset. This proportion, calculated using Equation (9) of Section 3.3.2, represented the significance or contribution degree accounted for by each group of CFKPIs on the performance management of the mine's operations. The 1st group explained 8.084% of the variation. This means that the 1st group of CFKPIs accounted for 8.084% of the impact on the performance management of the operations of the mine. The 2nd group accounted for 7.086% of the impact, followed by the 3rd group (7.004/%), 4th group (6.938%), 5th group (6.244%), 6th group (6.128%), 7th group (4.524/%), 8th group (4.344%), 9th group (4.236%), 10th group (3.820%), and 11th group (3.230%). These groups of CFKPIs formed a solid foundation for the SKPIs introduced in the next section. Table 3 summarizes the aforementioned individual and collective impact levels of the CFKPI groups on the performance management of the mine's operations. The extraction sums of squared loadings represent eigenvalues greater than one that determine the number of CFKPI groups to be created by the model. The rotated sums of squared loadings represent rotated factor loadings that illustrate the variance explained by each group of CKPIs.

Table 3. Total variance for the year 2015.

CFKPI Group	Extraction Sums of Squared Loadings			Rotated Sums of Squared Loadings		
	Total	% of Variance	Cumulative%	Total	% of Variance	Cumulative %
1	52.895	52.895	52.895	8.084	8.084	8.084
2	1.586	1.586	54.480	7.086	7.086	15.170
3	1.495	1.495	55.976	7.004	7.004	22.174
4	1.405	1.405	57.381	6.938	6.938	29.112
5	1.332	1.332	58.713	6.244	6.244	35.355
6	1.269	1.269	59.982	6.128	6.128	41.483
7	1.247	1.247	61.229	4.524	4.524	46.007
8	1.189	1.189	62.417	4.344	4.344	50.351
9	1.153	1.153	63.571	4.236	4.236	54.586
10	1.109	1.109	64.679	3.820	3.820	58.407
11	1.096	1.096	65.776	3.230	3.230	61.637

4.4.3. Smart KPIs

Each group of CFKPIs became an SKPI that was previously unknown, and CFKPIs in a group were treated as variables. Using Equation (10) of Section 3.3.3, the most dominating variables of each SKPI were measured, and the enterprise functions associated with the dominating variables (variables with the most variances or factor loadings) became the proprietors of the SKPI. An SKPI belonged to a single enterprise function if the dominating variables were from the same enterprise function or to more enterprise functions if more than one associated variable from different enterprise functions equivalently dominated that particular SKPI. Figure 12 depicts the SKPIs with associated variables, factor loadings, and enterprise functions.

The grouping of CFKPIs resulted in the creation of previously unknown SKPIs, with CFKPIs within each group being treated as variables. Utilizing Equation (10) of Section 3.3.3, we identified the most dominant variables within each SKPI and determined the associated enterprise functions. Specifically, the enterprise functions corresponding to the dominant variables (i.e., those with the highest variance or factor loadings) became the owners of the respective SKPIs.

An SKPI was assigned to a single enterprise function if the dominant variables originated from the same function. Conversely, an SKPI could be associated with multiple enterprise functions if multiple dominant variables from different functions exhibited equivalent influence on that particular SKPI. Figure 13 provides a visual representation of the SKPIs, including their associated variables, factor loadings, and enterprise functions.

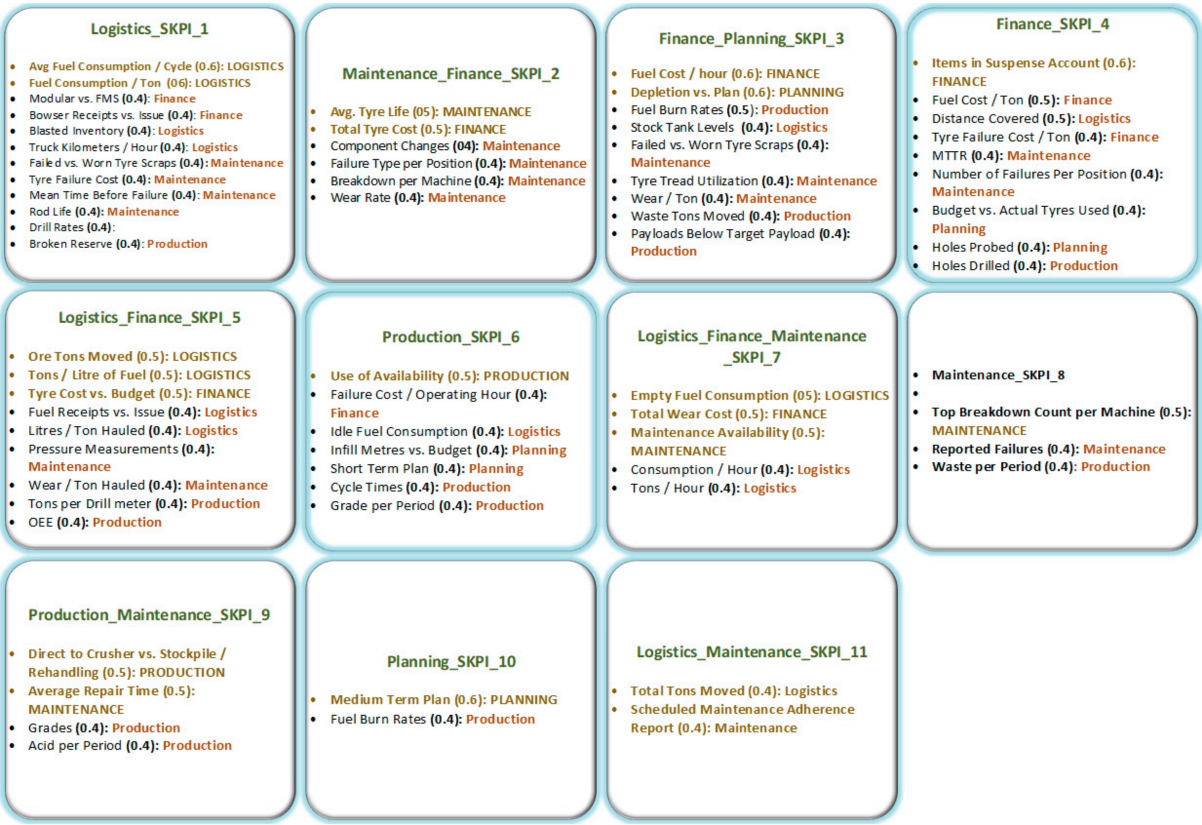

Figure 13. New SKPIs for the year 2015.

The analysis revealed the dominant enterprise functions associated with each SKPI. Specifically, the SKPIs were dominated by variables from the following enterprise functions: SKPI 1 (Logistics); SKPI 2 (Maintenance and Finance); SKPI 3 (Finance and Planning); SKPI 4 (Finance); SKPI 5 (Logistics and Finance); SKPI 6 (Production); SKPI 7 (Logistics, Finance, and Maintenance); SKPI 8 (Maintenance); SKPI 9 (Production and Maintenance); SKPI 10 (Planning); and SKPI 11 (Logistics and Maintenance). Figure 14 illustrates the new SKPIs in order of dominance for the year 2015.

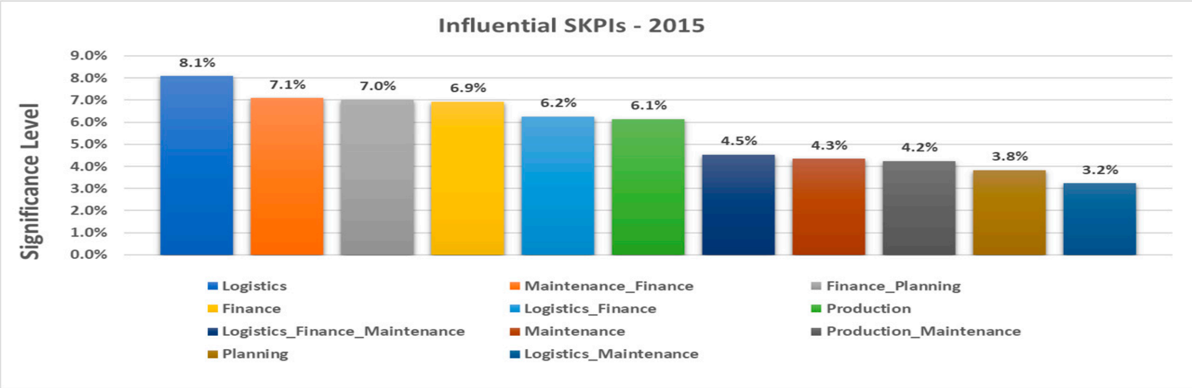

Figure 14. SKPIs' dominance order for the year 2015.

The mapping of SKPIs to their corresponding enterprise functions provided valuable insights into the correlations between SKPIs, variables, and enterprise functions. The dominant enterprise functions represented shared objectives that the variables within each SKPI strived to achieve. This is substantiated by the ID and CLD presented in Section 4.4.1. For instance, the most influential variables in the 1st SKPI originated from the Logistics enterprise function, as illustrated in Figure 11. The overarching goal of these variables was to optimize logistical planning accuracy, as depicted in Figure 8 of Section 4.4.1. Similarly, the 2nd SKPI's dominant variables belonged to the Maintenance and Finance enterprise functions, as shown in Figure 11. The common objective of these variables was to optimize maintenance adherence, thereby reducing unplanned and costly downtime, as illustrated in Figure 10 of Section 4.4.1. This analysis revealed precise correlations between dominant enterprise functions and the shared goals of variables within respective SKPIs.

Each SKPI comprised variables from multiple enterprise functions, each encompassing various business functions. These business functions, in turn, consisted of multiple processes across different organizational levels. Each process comprised several process steps, which utilize various resources. This hierarchical structure enabled the mine to pinpoint specific business functions, processes, process steps, and resources that required optimization to achieve the shared objectives of the variables within a particular SKPI.

By identifying the enterprise functions that encompassed the most dominant variables within SKPIs, the mine could focus its attention on the relevant business functions, processes, process steps, and resources. Furthermore, the SKPIs provided clarity on the intricate relationships between business functions, processes, process steps, resources, and their corresponding enterprise functions, thereby facilitating a more targeted approach to optimization and improvement.

4.5. Evolutions of SKPIs

The DDA model identified the primary drivers of the business by applying ML and AI techniques to the CFKPI dataset for the year 2015, as discussed in previous sections. When the same techniques were applied to the CFKPI datasets for 2016 and 2017, distinct business drivers emerged for each year. To ensure consistency, the same CFKPI names and quantities used in the 2015 dataset were applied to the 2016 and 2017 datasets. The only variation between the three datasets was the actual data values produced by these CFKPIs for each year. This approach guarantees that the model is driven solely by data generated by the mine's systems, rather than changes in the CFKPI names, count, or other factors.

Table 4 provides a summary of the key properties for each dataset, including the number of datapoints, t, df, p-value, KMO, total variance explained, top ten significant CFKPIs, and the resulting number of SKPIs.

Table 4. Dataset summary for the year 2015 to 2017.

Property	Year 2015	Year 2016	Year 2017
Datapoints	300,000	300,000	300,000
t-value (t)	−936,049.849	−976,670.406	−995,367.617
Degrees of freedom (df)	99	99	99
p-value	0.000	0.000	0.000
KMO	0.999	0.999	0.999
Total variance explained	0.616	0.696	0.677
Number of new SKPIs (factors)	11	11	11
Top 10 CFKPIs with highest business impact (communalities)	Average fuel consumption per cycle (0.774) Ore tonnes moved (0.730) Tonnes per drill metre (0.723) Scheduled maintenance adherence (0.717) Drill rates (0.714) Failed vs. worn tyre scraps (0.712) Cost vs. budget (0.711) Blasted reserve available (0.703) Depletion vs. plan (0.701) Modular vs. FMS (0.699)	Ore tonnes moved (0.872) Drill rates (0.844) Average fuel consumption per cycle (0.826) Tonnes per drill metre (0.819) Scheduled maintenance adherence (0.813) Cost vs. budget (0.791) Depletion vs. plan (0.771) Modular vs. FMS (0.759) Blasted reserve available (0.741) Failed vs. worn tyre scraps (0.739)	Tonnes per drill metre (0.795) Ore tonnes moved (0.751) Blasted reserve available (0.737) Scheduled maintenance adherence (0.728) Drill rates (0.718) Average fuel consumption per cycle (0.709) Failed vs. worn tyre scraps (0.705) Cost vs. budget (0.701) Modular vs. FMS (0.659) Depletion vs. plan (0.601)

Table 5 presents a summary of the SKPIs generated by the model for each year from 2015 to 2017. Figure 15 provides a comparison of the changes in business drivers between 2015 and 2017, illustrating how the business evolved and data shifted over time.

Table 5. Evolution of SKPIs from the year 2015 to 2017.

Year 2015		Year 2016		Year 2017	
SKPI	**Variance Explained**	**SKPI**	**Variance Explained**	**SKPI**	**Variance Explained**
Logistics_SKPI_1	8.084%	Finance_SKPI_1	9.084%	Production_SKPI_1	10.041%
Maintenance_Finance_SKPI_2	7.086%	Finance_Logistics_SKPI_2	8.086%	Production_Planning_SKPI_2	9.630%
Finance_Planning_SKPI_3	7.004%	Logistics_SKPI_3	7.938%	Finance_Logistics_SKPI_3	8.051%
Finance_SKPI_4	6.938%	Planning_SKPI_4	7.244%	Finance_SKPI_4	8.014%
Logistics_Finance_SKPI_5	6.244%	Production_SKPI_5	7.004%	Maintenance_SKPI_5	7.092%
Production_SKPI_6	6.128%	Production_Planning_SKPI_6	6.524%	Logistics Maintenance_SKPI_6	6.064%
Logistics_Finance_Maintenance_SKPI_7	4.524%	Finance Planning_SKPI_7	6.128%	Finance_Planning_SKPI_7	5.524%
Maintenance_SKPI_8	4.344%	Maintenance_SKPI_8	5.344%	Logistics_SKPI_8	4.072%
Production_Maintenance_SKPI_9	4.236%	Maintenance_Planning_SKPI_9	4.820%	Logistics_Planning_SKPI_9	3.741%
Planning_SKPI_10	3.820%	Logistics_Maintenance_SKPI_10	4.236%	Planning_SKPI_10	2.946%
Logistics_Maintenance_SKPI_11	3.230%	Logistics_Planning_SKPI_11	3.230%	Logistics_Finance_Maintenance_SKPI_11	2.537%

The DDA model reveals distinct business drivers for each year, from 2015 to 2017, by identifying the most significant CFKPIs and by generating new SKPIs as the business evolves and data change. The evolution of SKPIs over the three-year period provides valuable insights into the shifting priorities of the mine's operations. In 2015, during the start-up phase, logistical variables related to organizing and planning played a dominant role, with financial and integrated planning variables providing supporting functions. In 2016, as the mine expanded its operations and acquired more resources, financial management variables took centre stage, steering the business towards its objectives. Production, maintenance, and integrated planning variables played auxiliary roles during this period. By 2017, as processes matured and resources were utilized to near full capacity, production variables became the primary focus, driving efforts to achieve efficiency, reduced cycle times, customer satisfaction, and other key objectives. Financial management and integrated planning variables continued to provide essential support to production variables during this period.

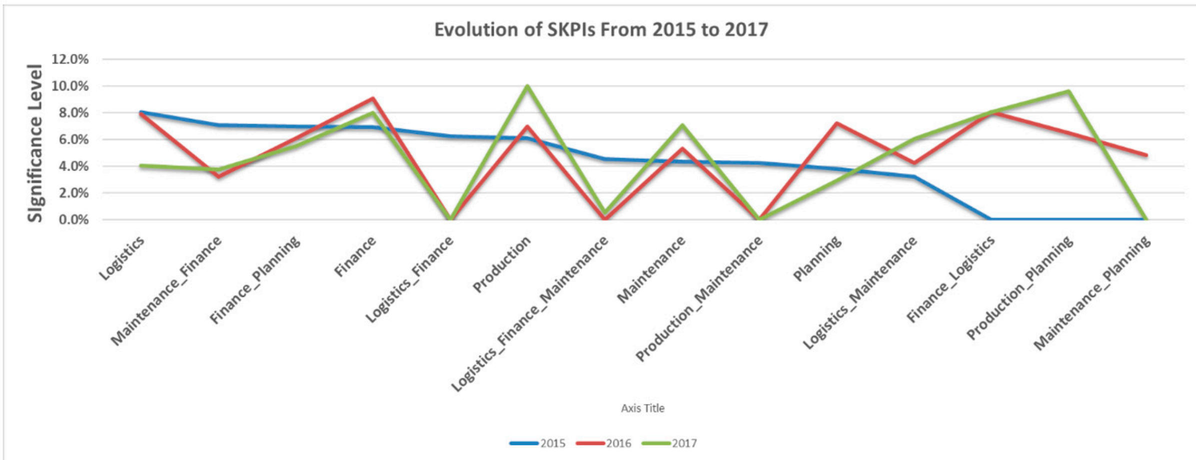

Figure 15. Evolution of SKPIs from the year 2015 to 2017.

5. Discussion

The DDA model complements rigid, traditional CFKPIs by validating data for correlations and adequacy; creating decision engines; enabling predictive analytics; discovering hidden data relationships, trends, and patterns; prioritizing CFKPIs; and consequently, creating SKPIs.

Discovering the properties of the CFKPIs enabled efficient troubleshooting through the adoption of the 5 WHYs root cause analysis technique. The root causes for performance predicaments were able to be traced from enterprise functions to business functions, processes, process steps, and resources. This enabled the mine to locate and optimize the components of the CFKPIs that caused underperformance. The mine was also able to determine the components of the CFKPIs that underpinned good performances and to pinpoint those components that required optimization. The properties were also used for predictive analytics by monitoring the performance of the CFKPIs' components and subsequently predicting the future outcome. This allowed the mine to act swiftly and optimize or replace the problematic components to avoid underperformance.

Creating fewer groups of CFKPIs reduced data complexity by revealing which CFKPIs were correlated and the nature of their correlations. The application of the ID and CLD techniques provided clarity on how the CFKPIs affected each other and how their correlations and interdependencies contributed to the performance of the business strategy.

Determining the significance level of each CFKPI to performance management helped the mine prioritize and pay appropriate attention to the right areas of the business. The conversion of CFKPI groups into SKPIs enabled each group to be treated and managed as a smart KPI that uses its variables and properties to manage performance. The association of enterprise functions to SKPIs provided deeper insights into the correlation between the dominant enterprise functions and respective variables. This ensured that the dominant enterprise functions shared common goals with the collaborating variables of SKPIs. The evolutionary nature of SKPIs enables the model to produce new SKPIs as business evolves and data change. This evolution of SKPI dynamically reveals the most influential variables and key business drivers. This would allow the business to align decisions to the actual, as opposed to supposed, business needs.

The performance of the model does not rely on human influence to discover the most influential variables and key drivers of the business; the model is purely data-centric. The elimination of human influence jettisons the dependency on individuals' experience and preferences in defining, prioritizing, and managing KPIs, which is the main purpose of this study. The creation of SKPIs prompts for a closer look at the main influencers of business performance. This study observed that logistic activities were pivotal during the start-up of the business. Financial management activities played a big role as more resources were acquired and utilized by the mine. Lastly, production operations contributed significantly to realizing efficiency, reduced cycle times, and enhanced customer satisfaction when operations had matured and resources were utilized effectively.

6. Conclusions

KPIs play a vital role in managing business performance. To be effective, KPIs must align with the overall business strategy. Traditional methods for defining, prioritizing, and managing KPIs rely heavily on process-driven automation, strict rules, and predefined configurations. This study introduces a novel data-driven model that harnesses ML and AI to define, prioritize, and manage KPIs based on business activities and internal and external influences. This approach creates intelligent, self-regulating KPIs that ensure businesses are measured and managed optimally.

Future research is necessary to test the effectiveness of this data-driven model across various business sectors, including Manufacturing, Agriculture, Banking, Finance, Healthcare, and more. This will help determine whether the model can be successfully applied beyond the mining sector, making it a versatile tool for businesses across different industries.

6.1. Research Implications

This study has significant implications for the field of business optimization. By introducing a new approach to KPIs that leverages data-driven automation techniques, this study presents a dynamic and adaptive model for creating smart KPIs that can adjust to changing business conditions. This model has the potential to enhance the resilience and responsiveness of business strategies, ensuring competitiveness and sustainability in an ever-evolving business landscape.

6.2. Practitioner Implications

This study discusses the advantages of the data-driven automation model over traditional methods of defining KPIs. This study shows how the model can complement the rigid and passive KPIs with flexible and intelligent SKPIs that can adjust dynamically to changes and can proactively manage performance. This study also shows how the model can provide deeper insights into the data patterns, correlations, and significance levels of the KPIs and how the model can reveal the main influencers and drivers of a business. This study concludes that the data-driven automation model can enhance the field of business optimization by introducing a new approach to KPIs that can help organizations achieve their goals and stay ahead of the competition. This study also suggests future research directions to test the model in various business sectors.

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References

1. Mohammadi, M.; Al-Fuqaha, A.; Sorour, S.; Guizani, M. Deep learning for IoT big data and streaming analytics: A survey. *IEEE Commun. Surv. Tutor.* **2018**, *20*, 2923–2960. [CrossRef]
2. Chang, D.; Chen, B.; Li, D.; Han, X. User Experience Oriented Mobile Business Process Optimization. *Stud. Inform. Control* **2014**, *23*, 171–182. [CrossRef]
3. Rondini, A.; Pezzotta, G.; Cavalieri, S.; Ouertani, M.; Pirola, F. Standardizing delivery processes to support service transformation: A case of a multinational manufacturing firm. *Comput. Ind.* **2018**, *100*, 115–128. [CrossRef]
4. Telukdarie, A.; Buhulaiga, E.; Bag, S.; Gupta, S.; Luo, Z. Industry 4.0 implementation for multinationals. *Process Saf. Environ. Prot.* **2018**, *118*, 316–329. [CrossRef]
5. Hu, B.; Feng, Y. Optimization and coordination of supply chain with revenue sharing contracts and service requirement under supply and demand uncertainty. *Int. J. Prod. Econ.* **2017**, *18*, 185–193. [CrossRef]
6. Yang, X.; Deb, S.; Fong, S. Bat algorithm is better than intermittent search strategy. *arXiv* **2014**, arXiv:1408.5348.
7. Mobin, M.; Mousavi, S.M.; Komaki, M.; Tavana, M. A hybrid desirability function approach for tuning parameters in evolutionary optimization algorithms. *Measurement* **2018**, *114*, 417–427. [CrossRef]
8. Dominy, S.C.; O'Connor, L.; Parbhakar-Fox, A.; Glass, H.J.; Purevgerel, S. Geometallurgy—A route to more resilient mine operations. *Minerals* **2018**, *8*, 560. [CrossRef]
9. Wang, S.; Cao, L. Inferring implicit rules by learning explicit and hidden item dependency. *IEEE Trans. Syst. Man Cybern. Syst.* **2017**, *50*, 935–946. [CrossRef]
10. Smith, M.L.; Wicks, S.J. Medium-term production scheduling of the Lumwana mining complex. *Interfaces* **2014**, *44*, 176–194. [CrossRef]
11. Himeur, Y.; Elnour, M.; Fadli, F.; Meskin, N.; Petri, I.; Rezgui, Y.; Bensaali, F.; Amira, A. AI-big data analytics for building automation and management systems: A survey, actual challenges and future perspectives. *Artif. Intell. Rev.* **2023**, *56*, 4929–5021. [CrossRef] [PubMed]
12. Krishna Vaddy, R. Artificial intelligence (AI) and machine learning driving efficiency and automation in supply chain transportation. *Int. J. Manag. Educ. Sustain. Dev.* **2023**, *6*, 1–20.
13. James, G.G.; Oise, G.P.; Chukwu, E.G.; Michael, N.A.; Ekpo, W.F.; Okafor, P.E. Optimizing business intelligence system using big data and machine learning. *J. Inf. Syst. Inform.* **2024**, *6*, 1215–1236. [CrossRef]
14. Yuen, M.C.; Ng, S.C.; Leung, M.F.; Che, H. A metaheuristic-based framework for index tracking with practical constraints. *Complex Intell. Syst.* **2022**, *8*, 4571–4586. [CrossRef]
15. Redchuk, A.; Walas Mateo, F. New Business Models on Artificial Intelligence—The Case of the Optimization of a Blast Furnace in the Steel Industry by a Machine Learning Solution. *Appl. Syst. Innov.* **2021**, *5*, 6. [CrossRef]
16. Bharadiya, J.P. Machine learning and AI in business intelligence: Trends and opportunities. *Int. J. Comput. (IJC)* **2023**, *48*, 123–134.
17. Choudhari, S.C.; Adil, G.K.; Ananthakumar, U. Choices in manufacturing strategy decision areas in batch production system–six case studies. *Int. J. Prod. Res.* **2012**, *50*, 3698–3717. [CrossRef]
18. Bharadwaj, A.; El Sawy, O.A.; Pavlou, P.A.; Venkatraman, N. Digital business strategy: Toward a next generation of insights. *MIS Q.* **2013**, *37*, 471–482. [CrossRef]
19. Nikolaou, I.E.; Tsalis, T.A. Development of a sustainable Balanced Scorecard framework. *Ecol. Indic.* **2013**, *34*, 3476–3486. [CrossRef]
20. Lourens, A.S.; Jonker, J.A. An integrated approach for developing a technology strategy framework for small-to medium-sized furniture manufacturers to improve competitiveness. *S. Afr. J. Ind. Eng.* **2013**, *24*, 50–67. [CrossRef]
21. Brundage, M.P.; Bernstein, W.Z.; Morris, K.C.; Horst, J.A. Using graph-based visualizations to explore key performance indicator relationships for manufacturing production systems. *Procedia CIRP* **2017**, *61*, 451–456. [CrossRef]
22. Kucukaltan, B.; Irani, Z.; Aktas, E. A decision support model for identification and prioritization of key performance indicators in the logistics industry. *Comput. Hum. Behav.* **2016**, *65*, 346–358. [CrossRef]
23. Naedele, M.; Chen, H.; Kazman, R.; Cai, Y.; Xiao, L.; Silva, C.V. Manufacturing execution systems: A vision for managing software development. *J. Syst. Softw.* **2015**, *101*, 59–68. [CrossRef]
24. Hsu, P.; Moore, J.A.; Neubaum, D.O. Tax avoidance, financial experts on the audit committee, and business strategy. *J. Bus. Financ. Account.* **2018**, *45*, 1293–1321. [CrossRef]
25. Cao, Y.; Zhao, K.; Yang, J.; Xiong, W. Constructing the integrated strategic performance indicator system for manufacturing companies. *Int. J. Prod. Res.* **2015**, *53*, 4102–4116. [CrossRef]
26. González-Gil, A.; Palacin, R.; Batty, P. Optimal energy management of urban rail systems: Key performance indicators. *Energy Convers. Manag.* **2015**, *90*, 282–291. [CrossRef]

27. Li, Y.; O'Donnell, J.; García-Castro, R.; Vega-Sánchez, S. Identifying stakeholders and key performance indicators for district and building energy performance analysis. *Energy Build.* **2017**, *155*, 1–15. [CrossRef]
28. Maschler, B.; Weyrich, M. Deep transfer learning for industrial automation: A review and discussion of new techniques for data-driven machine learning. *IEEE Ind. Electron. Mag.* **2021**, *15*, 65–75. [CrossRef]
29. Hao, H.; Zhang, K.; Ding, S.X.; Chen, Z.; Lei, Y. A data-driven multiplicative fault diagnosis approach for automation processes. *ISA Trans.* **2014**, *53*, 1436–1445. [CrossRef]
30. Furnham, P. Automation and autonomy of big data-driven algorithmic decision-making. *Contemp. Read. Law Soc. Justice* **2019**, *11*, 51.
31. Upadhya, R.; Kosuri, S.; Tamasi, M.; Meyer, T.A.; Atta, S.; Webb, M.A.; Gormley, A.J. Automation and data-driven design of polymer therapeutics. *Adv. Drug Deliv. Rev.* **2021**, *171*, 1–28. [CrossRef] [PubMed]
32. Goher, G.; Masrom, M.; Amrin, A.; Abd Rahim, N. Disruptive technologies for labor market information system implementation enhancement in the UAE: A Conceptual Perspective. *Int. J. Adv. Comput. Sci. Appl.* **2021**, *12*, 370–379. [CrossRef]
33. Madakam, S.; Holmukhe, R.M.; Revulagadda, R.K. The Next Generation Intelligent Automation: Hyperautomation. *JISTEM-J. Inf. Syst. Technol. Manag.* **2022**, *19*, e202219009. [CrossRef]
34. Gao, J.; Ploennigs, J.; Berges, M. A data-driven meta-data inference framework for building automation systems. In Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments, Seoul, Republic of Korea, 4–5 November 2015; pp. 23–32.
35. Abdulnour, S.; Baril, C.; Abdulnour, G.; Gamache, S. Implementation of industry 4.0 principles and tools: Simulation and case study in a manufacturing SME. *Sustainability* **2022**, *14*, 6336. [CrossRef]
36. Sishi, M.; Telukdarie, A. Digital integration of ERP to the sensor network for business optimization. In Proceedings of the International Annual Conference of the American Society for Engineering Management, Denver, CO, USA, 5–8 October 2022; pp. 1–9.
37. Nosalska, K.; Mazurek, G. Marketing principles for Industry 4.0—A conceptual framework. *Eng. Manag. Prod. Serv.* **2019**, *11*, 9–20. [CrossRef]
38. Szozda, N. Industry 4.0 and its impact on the functioning of supply chains. *LogForum* **2017**, *13*, 401–414. [CrossRef]
39. Margherita, E.G.; Braccini, A.M. Examining the development of a digital ecosystem in an Industry 4.0 context: A sociotechnical perspective. *SN Bus. Econ.* **2021**, *1*, 89. [CrossRef]
40. Munsamy, M.; Telukdarie, A. Process centric energy modelling for multinational manufacturing corporations. In Proceedings of the 2nd Industrial Engineering and Operations Management European Conference, Paris, France, 26–27 July 2018.
41. Taherdoost, H.; Sahibuddin, S.; Jalaliyoon, N. Exploratory Factor Analysis; Concepts and Theory. *Adv. Appl. Pure Math.* **2014**, *27*, 375–382.
42. Shamsalinia, A.; Moradi, M.; Farahani, M.A.; Masoudi, R.; Ghadimi, R.; Rad, R.E.; Ghaletaki, G.Z.; Ghaffari, F. Designing and psychometric evaluation of disease-related fear scale (D-RFS) in adults with epilepsy: A sequential exploratory mixed methods design. *Epilepsy Behav.* **2020**, *110*, 107169. [CrossRef] [PubMed]
43. Singh, M.; Rathi, R.; Garza-Reyes, J.A. Analysis and prioritization of Lean Six Sigma enablers with environmental facets using best worst method: A case of Indian MSMEs. *J. Clean. Prod.* **2021**, *279*, 123592. [CrossRef]
44. Balhara, Y.P.S.; Singh, S.; Saini, R.; Kattula, D.; Chukkali, S.; Bhargava, R. Development and validation of gaming disorder and hazardous gaming scale (GDHGS) based on the WHO framework (ICD-11 criteria) of disordered gaming. *Asian J. Psychiatry* **2020**, *54*, 102348. [CrossRef] [PubMed]
45. Rostami, F.; Osquee, H.O.; Mahdavi, F.; Dousti, S. Development of a New Psychometric Assessment Tool for Predicting Hepatitis B Virus Infection in Pregnant Women. *Int. J. Women's Health Reprod. Sci.* **2020**, *8*, 297–302. [CrossRef]
46. Bortolini, M.; Faccio, M.; Galizia, F.G.; Gamberi, M.; Pilati, F. Adaptive automation assembly systems in the industry 4.0 era: A reference framework and full–scale prototype. *Appl. Sci.* **2021**, *11*, 1256. [CrossRef]
47. Lins, T.; Oliveira, R.A.R.; Correia, L.H.; Silva, J.S. Industry 4.0 Retrofitting. In Proceedings of the VIII Brazilian Symposium on Computing Systems Engineering (SBESC), Salvador, Brazil, 5–8 November 2018; pp. 8–15.
48. Ferencz, K.; Domokos, J. Rapid prototyping of IoT applications for the industry. In Proceedings of the IEEE International Conference on Automation Quality and Testing, Robotics (AQTR), Cluj-Napoca, Romania, 21–23 May 2020; pp. 1–6.
49. Jankowska, B.; Götz, M. *Polish 2 Clusters. Economic Clusters and Globalization: Diversity and Resilience*; Routledge: London, UK, 2019; p. 27.
50. Woiceshyn, J.; Daellenbach, U. Evaluating inductive vs. deductive research in management studies: Implications for authors, editors, and reviewers. *Qual. Res. Organ. Manag. Int. J.* **2018**, *13*, 183–195. [CrossRef]
51. Benjamin, S.J.; Marathamuthu, M.S.; Murugaiah, U. The use of 5-WHYs technique to eliminate OEE's speed loss in a manufacturing firm. *J. Qual. Maint. Eng.* **2015**, *21*, 419–435. [CrossRef]

52. Czajkowska, A.; Ingaldi, M. Analysis of the impact of individual phases in the building process cycle on the environment with respect to the principles of sustainable development. *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *214*, 012012. [CrossRef]
53. Sahin, O.; Salim, H.; Suprun, E.; Richards, R.; MacAskill, S.; Heilgeist, S.; Rutherford, S.; Stewart, R.A.; Beal, C.D. Developing a preliminary causal loop diagram for understanding the wicked complexity of the COVID-19 pandemic. *Systems* **2020**, *8*, 20. [CrossRef]