Digital Technologies and Artificial Intelligence for Optimized Key Performance Indicators

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Abstract

Businesses define and manage Key Performance Indicators (KPI's). The most effective KPI's for business optimization is the subject of various studies. Various best practice bodies dedicate significant effort in defining smart KPI's. The Fourth Industrial Revolution (4IR) is able to digitalize the business so as to automate and collect data, facilitating digital constructs of defined KPI's. 4IR introduces Big Data (BD), Big Data Analytics (BDA) and Advanced Data Analytics (ADA) for analyzing data collected from digital business integration. ADA engine generates relationships between data never conceived historically. The ability of business to apply the theoretical correlations for business optimization is a contemporary challenge. Artificial Intelligence (AI) spawns mechanisms that enable machines to be intelligent enough to react like humans. However, there is a misalignment between KPI's defined by organizations and those discovered by analytics. This research proposes an approach to synergizing and developing smart KPI's by bringing together 4IR and traditional approaches.

Keywords
Industry 4.0, Advanced Data Analytics, KPI, AI, Digital Technologies.

1. Introduction

Business strategies are underpinned by planned objectives. The management and enhancement of these objectives is achieved through the implementation of Key Performance Indicators (KPI's) which specify, in detail, how to follow business goals (Propa and Goswami 2015). Crucially, vision and strategy should be defined more at a tangible level than at high level. This directs organizations in terms of making correct daily decisions. Proper and clearly defined vision helps an organization establish meaningful and constructive KPI's (Pérez-Fortes et al. 2016). Once identified by an organization, the vision and strategy should be interpreted, captured, and visualized into expressive KPI's for each organizational level, including the shop floor. Visual displaying of KPI's promotes regular performance dialog and day-to-day cross functional assessment between processes, maintenance, and engineering. Furthermore, displaying KPI's facilitates the escalation of some topics to weekly or monthly management meetings (Li et al. 2018).

Businesses; globally, small, medium and large define and manage KPI's. The most effective KPI's for business optimization is the subject of various studies. Several best practice bodies dedicate significant effort in defining smart KPI's (Jonsson and Rudberg 2017). The subjectivity and limitations of the KPI's to quantify business effectiveness remains a challenge.

The Fourth Industrial Revolution (4IR) technologies include the ability to digitalize the business to automate and collect data in order to facilitate digital constructs of defined KPI's. 4IR introduces Big Data (BD), Big Data Analytics (BDA) and Advanced Data Analytics (ADA), facilitating greater analysis of all data collected from digital business integration (Sackey and Bester 2016, Santos et al. 2017). The ADA engine generates relationships between data never envisaged in the past (Sackey and Bester 2016). The ability of business to apply the theoretical correlations for business enhancement is a modern challenge.

Artificial Intelligence (AI), an area of the Computer Science discipline, produces mechanisms that enable machines to be intelligent enough to react like humans. AI comprises various technologies including Machine Learning (ML) and Deep Leaning (DL) (Ai et al. 2018). Machines equipped with artificial intelligence encompass, amongst others, traits such as knowledge engineering, reasoning, perception, problem solving, planning, learning, ability to manage and move objects (Zhang et al. 2018). Currently, there is a misalignment between KPI's defined by organizations and those discovered by analytics. With its advanced technologies and mechanisms, AI could have capabilities to link the aforementioned atolls of KPI's. This paper propositions an approach to synergizing and developing smart KPI's by bringing together 4IR and conventional tactics.

2. Research Methodology

The KPI's explicitly identified and calculated at various levels of the business can be subjective. For example, the CEO of the company, with financial background or qualification, might take a financial approach when identifying KPI's. In contrast, if the CEO is an engineer, they could prioritize KPI's that depict operational efficiency in the organization. On the other hand, ADA uses statistical methods that do not have enough experience in working with strategic, tactical, and operational KPI's. This leaves the gap between explicitly defined KPI and ADA results. There is a need for mechanisms that would ensure that KPI's produced by ADA are in line with KPI's explicitly defined by business and explicitly-defined KPI's should agree with the ADA results. Therefore, this paper proposes an AI centric approach to resolve this contemporary challenge.

3. Literature Review

3.1. Performance Management

Performance Management System (PMS) aims to assess the organization's progress in terms of achieving the goals and objectives set. PMS focuses on both financial and non-financial aspects of the business and goes beyond measuring current performance but also enables for better and improved future performance (Propa et al. 2015). PMS is pivotal for the assessment of the organization's processes that create value to stakeholders and ensure efficiency in the transformation of resources into goods and services, quality of goods and services rendered, and the outcome of the organization's activities. PMS can also help organizations yield such pivotal results as enhanced motivation to perform, critical organizational objectives, development of staff competency and job descriptions (Li et al. 2018). To manage business activities and performance, several PMS's such as Knowledge Management (KM), Six Sigma (SS), Total Quality Management (TQM), Quality Program (QM), Internal Organization for Standardization (ISO), and Balanced Score Card (BSC) have been established (Jonsson and Rudberg 2017).

3.2. Big Data Analytics

Data volumes produced by many organizations have increased exponentially in recent times, while the price of data storage has been dwindling at the same time (Zhong et al. 2017). Data captured by various organizations include, but not limited to, data collected by sensors connected to smart devices, questionnaires, interviews' questions and answers, video, audio, workshops results, observations, process mappings, users' interactions, and social media content. This sudden increase in data production creates a need to construe and make sense of data (Sackey and Bester 2016). Big Data Analytics (BDA) is the means for collating and manipulating gigantic amount of structured and unstructured raw data from disparate sources into a consumable format for analysts and business as a whole. BDA is a process of analyzing huge and multifarious sets of data (i.e., Big Data) to expose unknown models, links, market changes, customer habits, and other key evidence to inform decision making (Vogel-Heuser and Hess 2016).

3.3. Machine Learning

Machine Learning (ML) is a technique that allows software applications to independently produce accurate results without explicit programming. ML builds algorithms that predict the future outcome by taking input data and applying statistical techniques (Zhang et al. 2018). ML adjusts the behavior of software applications by examining and looking for patterns in data. ML can be used for, amongst other things, fraud detection, predictive maintenance, and spam filtering (Ai et al. 2018). ML uses both supervised and unsupervised methods. A supervised method requires a provision of input, desired output data, variables and features to be studied and utilized by the model to yield predictions. The algorithm applies the learning outcome to new data thereafter. In contrast, unsupervised methods do not require training data with desired output. Unsupervised method uses more complex Deep Leaning (DL) iterative approach to produce an output (Ai et al. 2018, Chatzigeorgakidis et al. 2018). The ML process that employs supervised method, depicted by Figure 1, encompasses steps such as data identification and preparation, selection of ML algorithm, model development, training and deployment of the model.

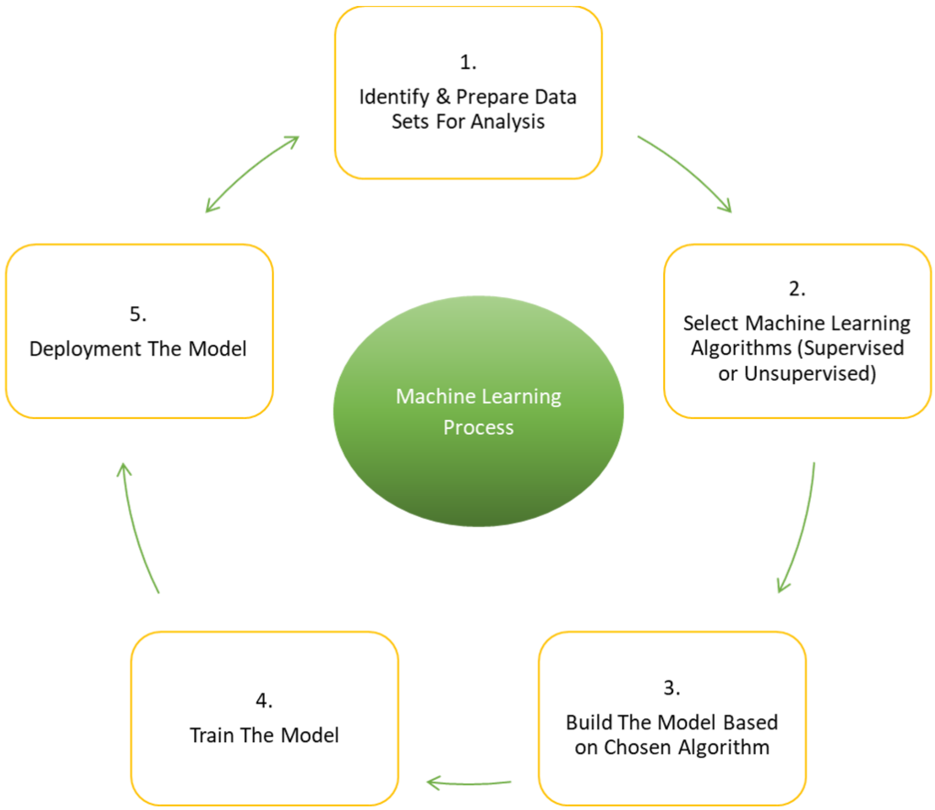

Figure 1. Machine Learning Process for supervised learning adapted from Ai et al. (2018)

3.4. Deep Learning

Deep Learning (DL), a feature of AI, is a technique used to simulate the way human beings gain knowledge (Zhang et al. 2018). The application of DL methods automates predictive analytics by using knowledge gained from prior processes to create new output. The predictive model becomes more complex and accurate with each iteration. This iteration goes on until a certain level of exactitude is achieved, hence the word deep in Deep Learning. DL is sometimes referred to as neural networking because of its nature of mimicking humans. DL requires access to large amount of learning data, both structured and unstructured (Zhong et al. 2017). A study by Li et al. (2018) claims that the emergence of enabling technologies such as Big Data, Internet of Things (IoT), and cloud computing has become significant to the implementation of DL. The process for building a DL model, depicted by Figure 2, comprises understanding of the business problem, data identification and preparation, selection of suitable algorithm, training and testing of the model on unstructured and unlabeled data.

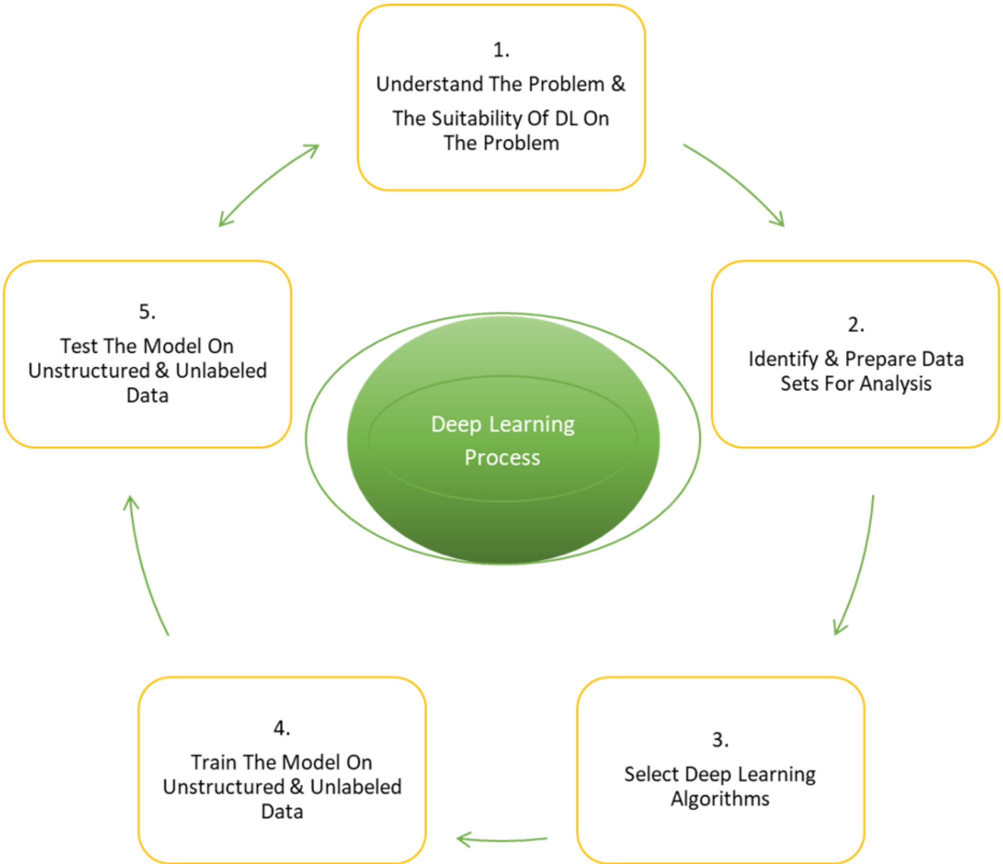

Figure 2. Deep Learning process as adapted from Zhong et al. (2017)

3.5. Supervised Learning

3.5.1. Regression analysis

Partial Least Squares regression
Studies (Mansouri et al. 2018, Serrano-Pallicer et al. 2018) declare that Partial Least Squares (PLS) regression technique is used in various areas such as nutrition science, social science, bioinformatics, environmental researches, chemometrics, and sundry engineering applications. Moreover, PLS regression is part of Multivariate (MVA) data treatment technique that facilitates the processing of raw data sets and interpretation of data structures in an eloquent context. MVA illustrates the relationship between dependent (response) and two or more independent (predictor) variables. This linear regression model is significantly used for the prediction of an unknown and unfamiliar variable. For example, the relationship between $\boldsymbol{x}$ and $\boldsymbol{y}$ can be deduced by the formula below.

$$y = b_0+b_1 x_1+b_2 x_2+\cdots+b_i x_i+\varepsilon$$

where $\boldsymbol{y}$ represents the values of observed response (output), $\boldsymbol{x}$ is the predictor values (input), $\boldsymbol{\varepsilon}$ is the difference of the observed output and projected values (residual), $\boldsymbol{i}$ is made of the number of independent variables; and $\boldsymbol{b}$ is the coefficient. The objective of PLS model is to identify $\boldsymbol{b}$ with least error $\boldsymbol{\varepsilon}$.

Relationship between variables
There are three significant characteristics of a relationship between variables; namely, shape, strength, and direction. The relationship strength denotes a degree to which the data points of two or more variables match. That is, the extent to which values on one variable can be deduced based on the matching values on another variable. For exploratory

approach, strength denotes the importance of the smooth versus the rough. The relationship is deemed strong when the data points are closer to the smooth and the rough is lesser (Hu et al. 2018).

Direction represents a positive and / or negative relationship. A positive relationship occurs when big values on one variable are related with the big values on another variable, and when small values on one variable are related with small values on another variable. A negative relationship occurs when there is a correlation between big values on one variable and small values on another variable, and between small values on one variable and big values on another variable (Lenz et al., 2018).

A single relationship can have more than one direction. For example, a relationship with a U shape changes from a negative to a positive direction. Therefore, the shape characteristic of a relationship is the manner in which variables are related to one another. That is, the shape of a line modelled by the smooth (positive and / or negative). The identification and analysis of a relationship characteristics are pivotal for the reason that the shape, strength, and direction of relationships can differ (Santos et al. 2017, Hu et al. 2018).

3.5.2. k-Nearest Neighbors

Classification
According to Zhang et al. (2018), when used for classification, *k*-Nearest Neighbors (*k*-NN) categorizes new items in a testing dataset (R) and reveals the closest neighbors for each element in a training dataset (S). This is achieved through resemblance quota extracted by a distance function such as Euclidean, Minkowski or Manhattan. In the study by Chatzigeorgakidis et al. (2018) to apply machine learning on Big Data via *k*-NN, Euclidean distance function was used to obtain, from *k*-NNs' classes, the dominant class for every query element in the testing dataset R (i.e., class membership). Zhang et al. (2018) claim that in *k*-NN classification, the class with high frequency compared to other nearest neighbors usually becomes the consequential class. This process is called a voting scheme and can be weighted when the distances between the nearest neighbors is taken into account. Consequently, the weight of every nearest neighbor is calculated based on its distance from the query element.

Regression
The process of calculating correlation between one derived variable and one or more stand-alone variables is called regression. Regression is categorized under supervised learning when studied from an ML perspective. Supervised learning techniques yield continuous values in contrast to discrete values such as labels, classes, categories, and many more produced by unsupervised learning (Serrano-Pallicer et al. 2018). The discrete values denote the forecasted value of the dependent variable. Regression methods are often used to prognosticate, from current or antique data, a variable's values such as consumption, prices, web page visits, and many more (Chatzigeorgakidis et al. 2018, Khakifirooz et al. 2018).

3.6. Unsupervised Learning

3.6.1. k-Means Clustering

Hedar et al. (2018) describes clustering as a process of creating sets (clusters) of analogous data points by splitting a pool of patterns. Patterns in one cluster are homogeneous to each other but different to patterns in other clusters. Clustering techniques has been used for many purposes such as retrieving information, extracting documents, classifying patterns, segmenting images, and many more. There are two categories of data clustering techniques, viz. hierarchical and partitional. Hierarchical clustering technique is the sequence of clustering depicted in a tree structure. Hierarchical techniques can take a bottom-up approach, commencing with each occurrence in its own structure and form a hierarchy of clusters by grouping together the most identical clusters. Alternatively, hierarchical methods can take a top-down approach, beginning with all instances in a single cluster and iteratively decomposing each cluster into smaller clusters. In contrast, partitional tactics do not create subsets; instead, objects are divided and grouped into non-overlapping clusters.

In the discipline of clustering, the most common clustering technique to finding structures in unlabeled data is *k*-Means algorithm. *k*-Means algorithm can be used to split several points of data into different groups. This algorithm performs unsupervised learning and does not require erstwhile familiarity with data. Moreover, *k*-Means algorithm is popular for its power to efficiently group big datasets. Nevertheless, the requirements to predefine the number of clusters and identify cluster elements in advanced are the major setbacks of *k*-Means algorithm (Lenz et al. 2018). According to Hedar et al. (2018), a few treatments have been devised to overcome the drawback of *k*-Means algorithm. These treatments include the intelligent *k*-Means method, known as *i*k-Means, that removes (one after another) abnormal examples from data in order to discover the number of clusters. Torti et al. (2018) define the 1st step of *k*-Means as the definition of K centroids, one for each cluster. By means of the centroids, the 1st clustering is formed by calculating the distance between each point and the centroid. A point is incorporated into a cluster that share a nearest centroid and each K centroid becomes the center of the cluster it represents. The iteration of this process ends when the distance between centroids and two continuous recurrences are less than the predefined limit or if the maximum iteration limit has been realized.

3.6.2. Principal Component Analysis

The primary goal of Principal Component Analysis (PCA) is to minimize intricacy (i.e., dimensionality) in a dataset that comprise a gigantic number of associated variables, while preserving most of the variation found in a dataset. This is attained by creating a new collection of variables, referred to as principal components (PC's), which are disparate from each other and classified so that the first few preserve largely the disparity found in all the original variables (Chatzigeorgakidis et al 2018). PCA is a linear technique used to reduce complexity and provides clear visibility while keeping the original variance of a dataset. The 1st PC preserves the biggest fragment of the disparity of the original collection and consequent PC's maintain progressively small segments not taken into consideration by the former PC's (Zhang et al. 2018).

An example adapted from Chaudhary et al., (2018) demonstrates PCA application as follows:

If $\boldsymbol{x}$ is a vector of $\boldsymbol{p}$ random variables and the aim is to find variances of $\boldsymbol{p}$, structure of the covariances, or simple the correlation between $\boldsymbol{p}$ variables. It would be difficult to discover these aspects by just looking at the data, unless the data structure is very basic and straightforward. An option would be to find $\boldsymbol{p}$ derived variables that encompass the majority of information from variances, relationships ,or covariances. It should be noted PCA pays more attention on variances; however, covariances and correlations are not totally disregarded. The 1st step is to find a linear function $\boldsymbol{\alpha'_1 x}$ of the aspects of $\boldsymbol{x}$ with highest variance, where $\boldsymbol{\alpha_1}$ is a vector of $\boldsymbol{p}$ constants $\boldsymbol{\alpha_{11}, \alpha_{12}, \ldots, \alpha_{1p}}$, and $\boldsymbol{'}$ means swap. The linear function is illustrated mathematically below.

$$\boldsymbol{\alpha}_1'\mathbf{x} = \alpha_{11}x_1 + \alpha_{12}x_2 + \cdots + \alpha_{1p}x_p = \sum_{j=1}^{p} \alpha_{1j}x_j.$$

Subsequently, a linear function $\boldsymbol{\alpha'_2 x}$ is devised, uncorrelated with $\boldsymbol{\alpha'_1 x}$ that comprise of highest variance. This is done to ensure that at the *k*th (last) stage a linear function $\boldsymbol{\alpha'_k x}$ comprising of lowest variance and not related to $\boldsymbol{\alpha'_1 x, \alpha'_2 x, \ldots, \alpha'_{k-1} x}$ is realized.

3.6.3. Association Rule Mining

Association Rule Mining (ARM) reveals appealing correlations amongst several variables in a dataset via association rules. ARM uses support and confidence measurements to discern significant rules in the database. The support and confidence are applied to choose the noteworthy rules. The purpose of support is to reveal the number of times items appears in the database, contingent on the regularity of another element in a transaction. Equally, confidence divulges the number of times the aforementioned statement is factual (Ai et al. 2018, Vogel-Heuser and D. Hess 2016).

Association rule technique was pioneered by Agrawal in 1993 (Bux et al., 2018). Consequently, it has since been employed for a number of purposes such as preservation of privacy, analysis of market-basket transactions, recommendation, health care, identification of hazard, to name but a few. A transaction dataset encompasses a sequence of n-transactions D = $(\mathbf{t_1, t_2, \ldots t_n})$. A transaction consists of a set of items I = $\{\mathbf{i_1, i_2 \ldots i_m}\}$ and a complete transaction is a combination of an itemset and a unique transaction ID (TID, $\boldsymbol{i}$). Itemset $\boldsymbol{i}$ is deemed common if Supp ($\boldsymbol{i}$) $\geqslant$ TS, where TS is the backing level outlined by the data miner. Supp ($\boldsymbol{i}$) denotes the support of itemset by depicting the occurrence frequency of itemset ($\boldsymbol{i}$) in the dataset. An association rule is illustrated as $\boldsymbol{a} \Rightarrow \boldsymbol{b}$, where $\boldsymbol{a}$ and $\boldsymbol{b}$ are two separate itemsets. The rule ***a*** => ***b*** implies that the presence of ***a*** indicates the presence of another ***b*** in a similar transaction with particular confidence.

4. Results and Discussion

4.1. Traditional KPI's

According to the literature, traditional KPI's are devised based on relevant stakeholders' experience and preferences. These KPI's are categorized in such taxonomies as operational, tactical and strategic. Operational KPI's are calculated from physical processes, intelligent devices, control systems, and Manufacturing Operations Management (MOM) systems. Tactical and strategic KPI's are derived from business systems such as Enterprise Resource Planning (ERP) and Business Intelligent (BI) respectively as depicted by Figure 3. Table 1 illustrates examples of KPI's in the aforementioned taxonomies.

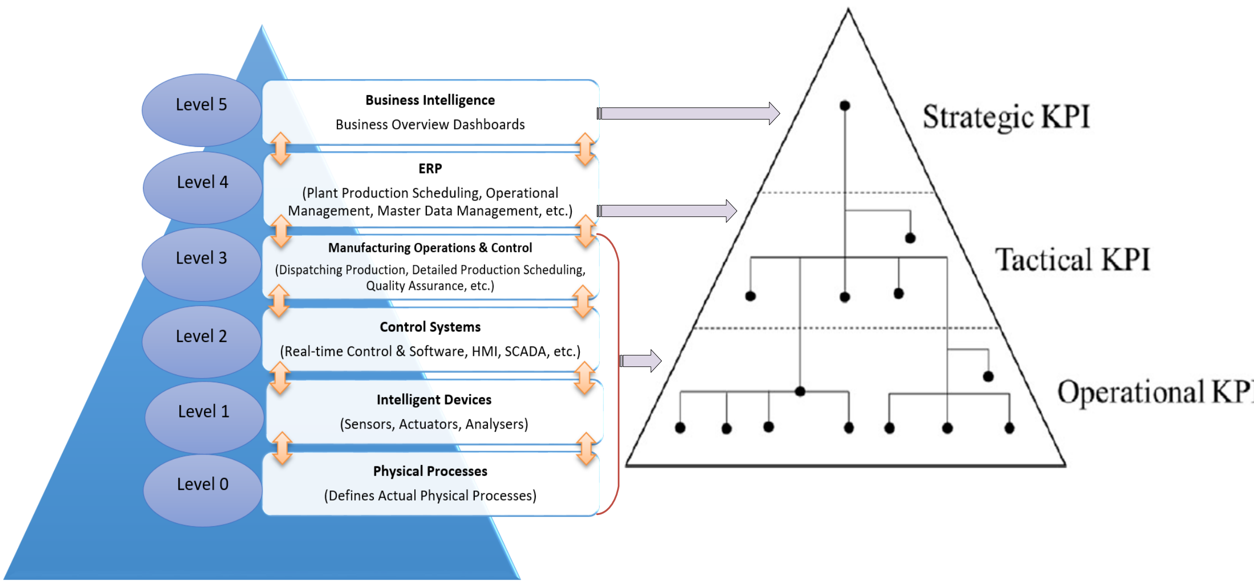

Figure 1. Business levels and KPI categories

Table 1. Taxonomies of KPI's

KPI Taxonomy	**KPI examples**
Strategic	Business overview, Financial Performance, Client Objective and Updates, Competitors Analysis, Future Roadmap, etc.
Tactical	Forecasting Accuracy, Customer Retention Rate, Customer Satisfaction Levels, Downstream In-Stock Ratio, Order Fill Rate, Record Accuracy, etc.
Operational	Employee Productivity, Production Actuals, Material Consumption, Equipment Availability, Equipment utilization, Execution % for Production, Lead-time, Availability etc.

Traditional KPI's are stored in relational databases and the relationships between the database objects (e.g., tables and views) are created by certain individuals (e.g., database design experts). Figure 4 depicts a relational database with relationships between objects created by the authors of this paper. It should be noted that the relationships are purely dependent on the designers' experiences, preferences, and discretions. This makes the KPI's and associated relationships very much subjective.

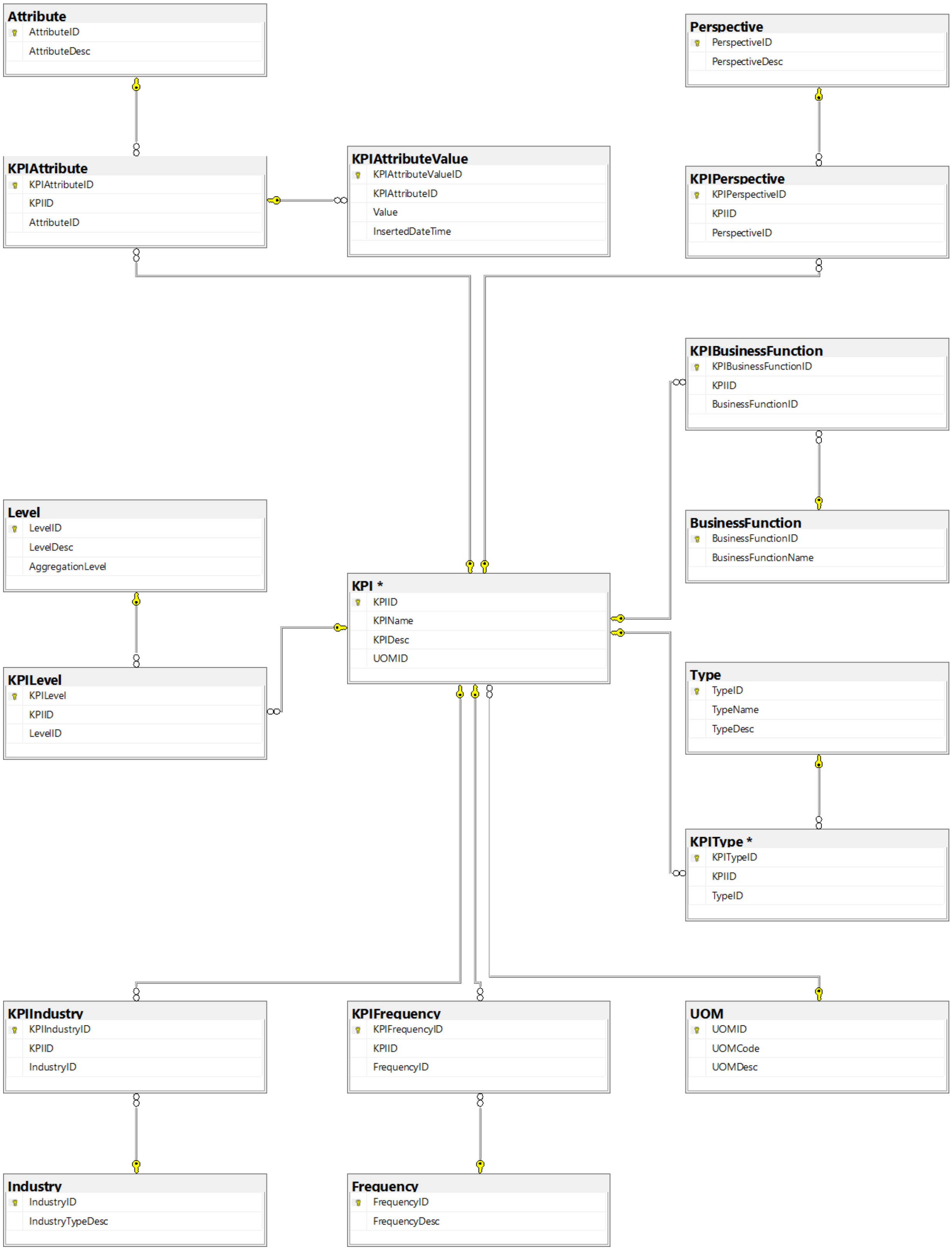

Figure 2. Relational database relationships

4.2. Creating AI Centric KPI’s

To create AI centric KPI’s, this paper suggests that the traditional, fixed structure (i.e., operational, tactical, and strategic) and database relationships be dismantled. Thereafter, one or more AI technologies such as regression, *k*-Nearest Neighbors, *k*-Means Clustering, PCA, ARM be applied on unstructured data. The purpose is to reveal the similarities and contrasts between traditional KPI’s and AI outcome. A new mechanism, merging traditional and AI methodologies, should be devised to bridge the gaps revealed by differences in the results. Thus, inventing robust mechanisms for creating optimized business KPI’s using digital technologies and AI.

4.3. Application of AI Technologies

This section provides suggestions on how different organizations can apply some of the AI statistical techniques, discussed in prior sections, to produce optimized KPI’s and consequently yield improved performance.

4.3.1. Classification

In a Customer Relationship Management (CRM) system, future customer behavior can be predicted by categorizing database records into various predefined taxonomies based on specific criteria. Some of the tools used for classification are decision trees, if-then-else rules, and neural networks.

4.3.2. Clustering

Insurance companies can use clustering to detect fraud; retail business can detect customers risk levels and retain customers; banks can categorize clients, perform credit scoring, and analyze customer profitability.

4.3.3. Prediction

Sales department can predict the demand for a product based on certain features, price, season, weekday or time, and customer gender. Sales figures can be foretold based on season, customer, product type, product feature, and region. Material consumption can be predicted based on shift, equipment type, equipment speed, and product produced. Equipment failure can be predicted based on equipment type, speed, running time, and product produced.

4.3.4. Regression

In manufacturing, a quality manager can comprehend the impact of different raw material types and quantity on the quality of the product produced. The impact on energy consumption based on day time or type of running equipment can be measured.

4.3.5. Principal Component Analysis

PCA could be used, for amongst other things, to reveal the cause of machine downtime. The causes could be poor maintenance plan, inadequate raw material, poor staff attendance, lack of expertise to operate a machine, and many more.

4.3.6. Association Rule

When a supermarket dataset comprising customers’ shopping transactions is used. It could be assumed that in the case where a customer purchases bread and butter, they will confidently purchase milk too; creating a possible association of {bread, butter} => milk.

4.3.7. Visualization

Organizations can provide the logical presentation of data by deciphering complicated characteristics into clear models for users to see the intricate patterns and relationships.

5. Conclusion and Future Research

This paper emphasizes the importance of clearly defining business strategy, converting strategy into goals and objectives, managing and monitoring the company performance (i.e., goals and objectives) by implementing KPI's. Moreover, the definitions and implementation of different AI and ADA statistical techniques are deliberated in detail. Consequently, the knowledge discovered creates the hypotheses that traditional, subjective KPI's could be supplemented by the application of AI and digital technologies that in turn utilize ADA statistical techniques significantly. Synergizing traditional with 4IR centric KPI's could reveal hidden patterns and relationships never conceived before in the organization.

This research can be expanded into a case study where traditional, structured dataset is identified, copied to a different repository, and dismantled into unstructured data. AI and ADA statistical techniques could be applied on unstructured dataset in order to create optimized KPI's and prove the theory presented in this paper.

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Biographies

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