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A hybrid forecasting model with logistic regression and neural networks for improving key performance indicators in supply chains

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ABSTRACT

This study investigates the potential of predictive analytics in improving Key Performance Indicators (KPIs) forecasting by leveraging Lean implementation data in supply chain enterprises. A novel methodology is proposed, incorporating two key enhancements: using Lean maturity assessments as a new data source and developing a hybrid forecasting model combining Logistic regression and Neural Network techniques. The proposed methodology is evaluated through a comprehensive empirical study involving 30 teams in a large supply chain company, revealing notable improvements in forecasting accuracy. Compared to a baseline scenario without process improvement data, the new methodology achieves an enhanced accuracy score by 17% and an improved F1 score by 13 %. These findings highlight the benefits of integrating Lean maturity assessments and adopting a hybrid forecasting model, contributing to the advancement of supply chain analytics. By incorporating lean maturity assessments, the forecasting process is enhanced, providing a deeper comprehension of the underlying Lean framework and the impact of its elements on supply chain performance. Additionally, adopting a hybrid model aligns with current best practices in forecasting, allowing for the utilisation of various techniques to optimise KPI prediction accuracy while leveraging their respective strengths.

1. Introduction

Advancements such as Industry 4.0, Big Data Analytics (BDA), Artificial Intelligence (AI), and its subsets such as Machine Learning (ML) and Neural Networks (NN), present significant opportunities for improving Supply Chain Performance through the application of Supply Chain Analytics. One significant output as a result of the advancements is enhanced forecasting of Supply Chain Performance using Lean maturity assessments.

The utilisation of improvement frameworks such as Lean, Six Sigma, Lean Six Sigma (LSS) and Total Quality Management (TQM) is widely used in the optimisation of business performance within Supply Chains. The level of "leanness" or Lean Maturity is frequently evaluated by Supply Chain teams using descriptive analytics to better understand the historical trends within their organisations [1–3].

Using Lean Maturity however in Predictive Analytics in Supply Chains is still in its infancy. We classify Predictive Analytics to form part of the wider area of data analytics. With Predictive Analytics to focus specifically on using statistical methodologies and forecasting to know what is likely to happen in future [4]. Only a handful of articles were identified that applied Predictive Analytics with TQM assessments [5,6], however none have been found for Lean or LSS data sets. This potentially provides us with an opportunity to identify which Lean framework elements exert the greatest impact on performance outcomes [7,8].

This article therefore presents a methodology aimed at enhancing the prediction accuracy of binary Key Performance Indicators (KPIs) in the domain of SCM. The methodology leverages two innovative approaches to achieve this goal. Firstly, it incorporates data obtained from Lean maturity assessments into a proposed forecasting model. By utilising insights derived from these assessments, which offer valuable information on process improvements, the model can identify potential future changes in performance.

Secondly, the methodology employs a hybrid forecasting model that combines regression techniques with NN. This hybrid approach draws from established forecasting methodologies utilised in diverse domains such as national electricity consumption demand [9] and stock price predictions [10], integrating best practices and the latest trends in forecasting and ML.

The paper summarises the output from a study which was conducted with a large-scale Supply Chain organisation with a workforce exceeding

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10,000 employees. In this organisation teams regularly engage in Lean maturity questionnaires in each of their respective departments. The organisation maintains a centralised record system, from which the dataset was accessed and utilised as a primary data source for this study.

Utilising these questionnaires, predictions were made regarding the teams' ability to meet delivery targets in the upcoming months. This particular performance KPI is binary, with a pass or fail value assigned to specific months. Accurate measurement and analysis of this delivery KPI are of paramount importance for effective supply chain planning. The reliability of this KPI data plays a pivotal role in mitigating potential disruptions within the supply chain. Accurate predictions allow supply chain managers and decision-makers to proactively identify underperforming areas and take corrective actions to ensure smooth operations and meet customer expectations.

Then KPI forecasting was performed for a cohort consisting of 30 teams to predict the KPI value for the following month. Five prediction models were generated for each team: (1) univariate logistic regression model, (2) multivariate logistic regression model, (3) Multi-layer Perceptron (MLP), (4) gradient boosted model and (5) a hybrid model. Performance metrics, including accuracy scores measuring the overall correctness of predictions, and F1 scores accounting for the balance between precision and recall, were employed to comprehensively evaluate the effectiveness of prediction models.

This study makes substantial contributions to the domain of Supply Chain Analytics. Firstly, it identifies an untapped data source that exists abundantly in numerous supply chains. By incorporating lean maturity data, we potentially can enhance the forecasting performance capability in the Supply Chain.

Secondly, this study highlights that a novel forecasting methodology utilising a hybrid model, has the potential to further enhance KPI predictions. The accompanying empirical investigation demonstrates tangible improvements in delivery forecast accuracy scores by 17 % and F1 scores by 13 %, directly attributable to the implementation of the proposed approach in this paper.

In this paper we present a literature review covering Lean Assessments, Process Improvements, and their potential usage as a data source to be used in Forecasting. We then proceed to present a methodology of the newly proposed data sources, and with 5 predictive models. Followed by results of using the predictive models, which are then explored in more detail in the discussion section, followed by our conclusions and recommendations.

2. Literature review

This literature review encompasses three distinct Section (1. Process Improvements and Lean Maturity, 2. Forecasting and 3. Research Gaps and Highlights). The first section explores the concept of Lean Maturity and also highlights the limited number of studies conducted on Predictive Analytics specifically focused on leanness.

The second section delves into the realm of forecasting, placing a significant emphasis on the identification of best practices and the exploration of recent research trends. This comprehensive examination of forecasting techniques and methodologies is of paramount importance since the inclusion of maturity assessments in the predictive model fundamentally transforms the nature of the problem. It shifts from a traditional univariate forecasting approach, which solely relies on past KPI data, to a more complex multivariate forecasting framework that incorporates both past KPI data and past maturity assessment data. This distinction necessitates a thorough exploration of the latest advancements in the forecasting literature to ensure the accurate modelling of this augmented problem domain.

Lastly, the review will identify how the present study contributes to the advancement of supply chain analytics. By bridging the aforementioned gaps in the literature, the current research enhances the understanding of predictive analytics applied to process improvements in Supply Chain Management. Through its unique approach of incorporating lean maturity assessments into the forecasting model, this study adds a novel perspective to the field, providing valuable insights and contributing to the existing body of knowledge in supply chain analytics.

2.1. Process improvements

"Process Improvement" refers to the systematic examination and enhancement of processes within an organisation. A number of improvement methodologies have been well established, including Lean, Six Sigma, LSS, TQM, the Kano Model, Quality Function Deployment, and Taguchi's Quality Loss Function. Despite their differences, these methodologies share a common goal: to minimise waste in business operations and concurrently enhance customer satisfaction and financial performance [1,2].

Lean in manufacturing is a widely adopted improvement methodology that prioritises the addition of value to business customers and elimination of waste in production processes. The methodology is equipped with a variety of tools and techniques, such as Value Stream Mapping (VSM), Kanban, Kaizen, 5S, Just-in-Time, and Total Productive Maintenance. Lean is considered a modern advancement in manufacturing, drawing inspiration from Henry Ford's mass production principles and rooted in the Toyota Production System of the 1930–1960s [11,12].

Six Sigma is another widely used improvement methodology, focused on reducing process variability to reduce defects, improve customer satisfaction, increase business profits, and boost employee morale. The methodology was developed by Motorola in 1979 in response to quality issues and was popularised through a consulting company, Six Sigma Academy, and a contract with General Electric in the mid-1980s [13]. Six Sigma makes use of tools such as control charts, statistical process control, and Failure Mode and Effects Analysis (FMEA). The methodology also features certifications, known as "Black Belts," to recognise proficiency in its principles, tools, and techniques.

Lean and Six Sigma, despite originating as separate methodologies, share the common objective of improving business efficiency. As such, the two have been combined into LSS [14,15].

TQM, originating in the 1980s, represents a quality improvement initiative that sought to promote quality enhancement across the entire organisation, at all levels and functions. The methodology was greatly influenced by companies in the USA and Japan and led to the development of industry standards for quality management systems (QMS), such as ISO 9001:2015 and AS9100 [16].

The Lean maturity of an organisation can be evaluated through various approaches, with the most common being assessments, surveys, and questionnaires [17]. These assessments often consist of categorical data and a set of questions aimed at gauging the implementation of Lean practices, such as VSM, 5S or Kanban. Another approach to measure Lean maturity is through efficiency metrics, which are usually continuous in nature and relate to specific projects, processes, departments, or the entire organisation. Examples of these metrics include the cost of Work in Progress (WIP), machine downtime, utilisation of space and transport, percentage of rework, and lead-times. These metrics can be used for monitoring progress, continuous monitoring after improvement implementation, and benchmarking between different areas [18].

2.2. Forecasting

To promote advancements in the field of forecasting, the M-Competitions in Time Series have provided researchers and practitioners with a platform to evaluate the effectiveness of different approaches. The main trend observed in the 2018 M4 competition was the emergence of hybrid techniques. Participants achieved impressive results by integrating multiple statistical methods and often incorporating ML techniques. While pure ML approaches did not achieve the highest performance, the combination of traditional statistical forecasting methods with ML techniques demonstrated improved accuracy. The findings of the M4 competition shed light on the significance of blending different forecasting methods, like combining traditional statistical and ML approaches [19]. The M5 competition conducted in 2020 further substantiated the advantages derived from integrating diverse forecasting methods, although in this instance, ML algorithms emerged as the dominant performers [20].

The utilisation of hybrid forecasting models has gained traction in recent years, despite its roots dating back to the early 2000 s. An early milestone in this field was Zhang's 2003 study [21], which amalgamated the widely used autoregressive integrated ARIMA models with NN, demonstrating the superiority of hybrid models over separate ARIMA and NN approaches. In contemporary research, there is a discernible surge in the adoption of hybrid models to bolster forecast precision, as evidenced across diverse domains including national electricity consumption demand [9], building energy consumption [22], electricity price forecasting [23], short-term load prediction [24], solar radiation [25], water pollution [26], and stock price predictions [10].

In supply chain domain, a hybrid forecasting model was developed in 2022 study by Siddiqui et al. [27] that combines the ARIMA and Holts-Winter models for accurate demand forecasting within pharmaceutical supply chains. Additionally, in the same year, Feizabadi [28] employed a hybrid approach, integrating the ARIMAX model with NN, to enhance demand forecasting within the steel industry. These instances underscore the versatility and effectiveness of hybrid forecasting techniques across diverse industrial sectors.

While the adoption of hybrid forecasting models has undeniably expanded and yielded promising results across numerous fields, including supply chain, it is important to acknowledge some critical considerations. First, the effectiveness and suitability of hybrid models may depend on the specific problem domain and dataset. What works well in one context may not be equally successful in another.

Furthermore, the complexity involved in developing and fine-tuning hybrid models cannot be understated. These models, as demonstrated in the aforementioned studies, require proficiency across multiple domains. For instance, the skillset required to construct statistical forecasting models such as ARIMA and Holt-Winters is distinct from that needed for traditional ML models like Random Forests and Gradient Boosted Trees. Additionally, the development of NN represents yet another intricate skillset.

To mitigate the initial concern regarding domain specificity, we initiated our investigation by searching for studies that tackle analogous issues and utilise comparable datasets. Although we did not identify any supply chain research specifically employing binary KPIs, our quest yielded several relevant papers that focused on categorical predictions. These findings are presented in Table 1. To alleviate the apprehension regarding model complexity, we opted to adopt the prevailing approach from previous studies on categorical forecasting.

In the field of forecasting, the comparison between univariate and multivariate techniques is another important subject in the literature. Univariate forecasting relies solely on historical data, while multivariate forecasting incorporates additional variables to improve accuracy by capturing dependencies. Several studies have investigated the performance of these models across different domains. In a 2021 study by Miller and Kim [35] on cryptocurrency prediction, various ML methods were employed, demonstrating that the multivariate approach outperformed univariate methods in terms of accuracy. Similarly, Pierdzioch and Risse [36] studied forecasting for precious metal prices using a multivariate model, revealing its superiority over univariate forecasts. Furthermore, Rana et al. [37] examined the forecasting of electricity power generated by solar PV systems and found that both univariate and multivariate models exhibited comparable accuracy. These findings suggest that the utilisation of multivariate techniques should be explored when suitable data is available, as it can enhance forecasting accuracy.

Table 1
The hybrid models for categorical forecasts.

Authors	Applied hybrid model	Summary
Silva et al.[29]	ML algorithms such as Random Forests, Naïve Bayes and MLP	Silva et al.[29] proposed a hybrid 24-hour forecasting model for severe convective weather, employing ML algorithms such as Random Forests, Naïve Bayes and MLP to enhance the accuracy of severe weather predictions.
Alqadhi et al. [30]	Logistic regression, MLP, Random Forest, M5P, Support Vector Machine (SVM)	Alqadhi et al.[30] conducted a study to optimise ML models for landslide susceptibility mapping. Their most effective model involved a hybrid ensemble combining logistic regression, MLP, Random Forest, M5P and SVM algorithms and successfully identified risk zones and sensitive parameters contributing to landslide events.
Munkhdalai et al.[31]	MLP and logistic regression	In 2019, Munkhdalai et al.[31] proposed a credit scoring model that combined MLP and logistic regression techniques. The hybrid model outperformed baseline models across benchmark datasets for the identification of high-risk borrowers.
Zhu et al.[32]	Logistic regression and radial basis function (RBF)	Zhu et al.[32] developed models for assessing the credit risk of small and medium-sized enterprises in China's supply chain financing sector. Their study encompassed logistic regression and RBF hybrid models for forecasting credit risk.
Tunç[33]	Logistic regression and MLP	Tunç[33] introduced a novel hybrid approach by merging logistic regression with MLP for the analysis of lung cancer data. This method demonstrated superior performance compared to standalone logistic regression and NN models.
Tsai and Chen [34]	Logistic regression and MLP	Tsai and Chen[34] conducted a comparative analysis of various hybrid models in the development of credit rating systems. Their study revealed that the combination of logistic regression and MLP achieved the highest prediction accuracy. They employed a real-world dataset from a bank in Taiwan for their investigation.

2.3. Research gaps and highlights

To date, no studies have been identified that analyse Lean maturity assessment data through Predictive Analytics. In contrast, there have been several studies which have looked into assessments from process improvement frameworks apart from Lean maturity. For instance, Sila et al. [5] used surveys from a large number of Turkish companies to determine if there was a positive effect of TQM on organisational effectiveness, financial performance, and market results, through the use of NNs.

The above-mentioned study suggests that process improvement surveys can be used effectively as a data source to predict future business performance. However, there are two limitations to this study: first, the findings were based on surveys from multiple companies in Turkey, which may result in potential bias in responses. Secondly, no analysis was conducted to determine whether forecasting using process improvement data is superior to models without such data.

In another study, Mansoursamaei et al. [6] developed an NN model using responses from TQM questionnaires to employees. The study aimed to evaluate TQM within an organisation and demonstrated that the model's output could predict the quality of operations. The study also did not review whether forecasts based on TQM data outperform forecasts without TQM data.

From these mentioned studies, two key observations can be made. Firstly, there is evidence that suggests process improvement data can be used for predictive analytics to forecast business performance. However, it is unclear whether models using process improvement data are superior to simpler forecasts without such data. To address this limitation, the current study will compare forecasts with and without improvement data to determine the value of the new data source. Secondly, the literature highlights that TQM data is being explored for predictive analytics, but Lean has not been covered yet. To address the gaps and weaknesses identified in the papers, the present study will undertake an empirical investigation within a large-scale supply chain company. This research aims to contribute to the existing knowledge by filling the identified gap in understanding.

Within the context of a literature review focused on process improvement maturity assessments, the absence of research was identified in the realm of predictive analytics, particularly within the sphere of Lean methodologies. While the literature presents several papers in the TQM field, a noticeable lack of studies solely dedicated to Lean practices prevails. Motivated by these observations, the central objective of this study is to improve the field of supply chain analytics by utilising a new data source: Lean maturity assessments.

The literature review has helped to identify two key enhancements to the methodology, aimed at refining categorical KPI forecasting within supply chains: the utilisation of multivariate forecasting techniques and the incorporation of hybrid forecasting models.

Firstly, the literature emphasises the significance of exploring the benefits of multivariate forecasting approaches. To contribute to this exploration, we introduce a novel dataset. Our study leverages Lean maturity assessment data as a resource to elevate the precision of KPI forecasting within the supply chain domain. Rigorous validation is ensured through a comparative analysis between univariate and multivariate forecasting methods.

Secondly, the forecasting literature underscores the diversity of hybrid forecasting techniques, tailored to diverse domains and datasets, each requiring a nuanced skill set. This landscape encompasses both conventional methods like ARIMA models and innovations like NN.

Considering these findings, studies focused on categorical forecasting were reviewed. Predominantly, prior studies have leaned towards the utilisation of logistic regression and MLP models. This approach was adopted to our supply chain area of KPI forecasting.

In summary, this study aspires to make two substantial contributions to the field of supply chain analytics. Firstly, by focusing on underutilised Lean maturity assessment data, we aim to determine whether our multivariate approach surpasses the conventional univariate methods. Secondly, by adapting hybrid models, acknowledged as industry best practices in forecasting, we aim to significantly enhance forecast accuracy within the domain of supply chains.

3. Methodology

In this section, we present the methodology employed in our study, which seeks to address a pressing problem in the realm of supply chain management—enhancing the accuracy of KPI forecasting. Our central research question is as follows: "To what extent can the integration of Lean maturity assessments as a data source and the adoption of a hybrid forecasting model improve KPI forecasting accuracy in supply chain enterprises?".

The problem at hand is the inherent challenge of achieving reliable KPI forecasts within the complex landscape of supply chain enterprises. To tackle this problem, our methodology is structured around the following key objectives:

1. Assessing the feasibility and effectiveness of incorporating Lean maturity assessments as a data source for KPI forecasting in supply chain management. This objective stems from the recognition that traditional forecasting methods often fall short in capturing the nuanced dynamics of supply chain performance.
2. Developing and implementing a hybrid forecasting model that amalgamates Logistic regression and NN techniques. This approach is designed to address the problem of inadequate prediction precision, which is a common hurdle faced by supply chain professionals seeking to make informed decisions.
3. Conducting an empirical evaluation of our methodology using data sourced from a sizable supply chain organisation consisting of 30 distinct teams. This evaluation aims to provide concrete evidence of the improvements achieved in forecasting accuracy through the application of our methodology, thus offering a potential solution to the problem of unreliable KPI forecasts.

The methodology consists of 3 steps. First, we cover preparing the data. Then, several models were built for each team. Finally, the models were compared using appropriate measures. All models were build using Python. The methodology for this study was heavily influenced with previous studies using hybrid models. Adapting the common approach, it was decided to build a Logistics Regression Model and NN model.

3.1. Prepare the data

In our study, the data was gathered from 30 teams over a span of 5 years, where maturity assessments and delivery scores were recorded on a monthly basis. The data is organised in a tabular format, comprising both the label and the features. The label refers to the variable that we aim to predict, such as the delivery value, while the features encompass supplementary data that can assist in predicting the label.

The first set of features pertains to the date of the observation, including variables like the month number or the year of the assessment. These features can prove valuable when there are monthly, or yearly seasonal patterns inherent in the data. By incorporating these date-related features, we can capture any cyclic patterns or trends that may exist within the dataset.

Another set of features is based on lags, which represent the values of the label or a feature for previous assessments. These lagged features allow us to take into account the historical values of the label and features, enabling us to assess how past values may influence the current prediction. By considering these lagged features, we can potentially capture any time-dependent dependencies or trends that might impact the forecasting model.

Finally, it is necessary to partition the data contained in the table into two distinct samples: the training sample and the test sample. The training sample is employed in the process of constructing forecasting models, while the test sample is utilised for evaluating the accuracy of these models. In the training phase, we utilise the oldest 80 % of the available data, reserving the most recent 20 % for testing purposes.

3.2. Develop forecasting models

Based on the analysis of existing literature, the primary models utilised in this study are regression models and NN models. For each team under investigation, a set of models has been constructed, including regression models, dedicated NN models, and hybrid models that combine elements of both approaches. Each model was optimised using hyperparameter tuning and cross validation.

The linear regression algorithm models the relationship between input features and an output label by fitting a linear equation to observed data. A regression equation expresses how a set of factors explains an outcome and how the outcome changes with each factor. For example, the relationship between features and a continuous label can be described using a regression equation [38].

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k \tag{1}$$

The above equation exemplifies a Multiple Regression Model, where the variable Y represents a label, and the variables X_k denote features. The coefficients $\beta_1 \ldots \beta_k$ pertain to the explanatory variables, whereas β_0 corresponds to an intercept term.

Regression analysis can also be applied to binary data using logistic regression. In this case the Y term in the previous regression equation can be substituted with the probability of a delivery outcome. By doing so, one can construct a logistic regression model, as outlined by Berk [39].

$$Ln\left(\frac{P}{1-P}\right) = \beta^0 + \beta^1 X^1 + \beta^2 X^2 + \ldots + \beta_k X_k \tag{2}$$

An artificial neural network, or neural network, is an interconnected collection of weighted nodes that simulate the behaviour of biological neurons. The simplest architecture is the Single-Layer Perceptron, which has a single layer of neurons connected directly to input features. It applies a weighted sum and an activation function to generate a linear decision boundary. To handle more complex patterns or nonlinear relationships, more complex architectures are used, like MLPs. MLPs have multiple layers, including input, hidden, and output layers, with nodes connected by weights. By optimising their weights through an objective function, MLPs can learn and model intricate data relationships. MLP was the most common NN architecture in the literature review. Despite the capability of MLPs to capture complex patterns, they are subject to significant limitations. Primarily, MLPs can exhibit overfitting, where they excessively adapt to the training dataset, resulting in reduced generalisation performance on unseen data. Additionally, discerning the relative importance of features within an MLP can be challenging, hindering the interpretability of the model [32–34].

Hybrid models, which involve the combination of various algorithms such as a blend of logistic regression and MLP, offer diverse approaches for integration. For instance, 2019 study devised three separate neural network models that were subsequently merged using logistic regression [31]. Other investigations from the literature review adopted an alternative sequence by initially constructing a logistic regression model and subsequently feeding its outputs into a NN model. This hybrid methodology yields several advantages. The initial step involving logistic regression facilitates the identification of significant features and generates its own label predictions. Subsequently, the neural network stage is dedicated to detecting complex patterns exclusively using the key features [32–34].

To evaluate the effectiveness of our proposed regression and NN models, we introduced an additional model that utilises gradient boosting techniques. Specifically, we incorporated the highly regarded eXtreme Gradient Boosting (XGBoost) algorithm into our suite of models for evaluation. XGBoost constructs an ensemble of decision trees, with each new tree working to rectify the errors of the previous trees.

$$\mathrm{Obj} = \sum\nolimits_{i=1}^{n} l(y_i, \hat{y}_i) + \sum\nolimits_{k=1}^{K} \Omega(f_k) \tag{3}$$

The above equation represents the objective function of XGBoost as a combination of a loss function l and a regularisation term $\Omega(f_k)$. n is the number of training examples and K is the number of trees [40].

It is worth mentioning that XGBoost is a widely accepted algorithm with applications in various domains, including but not limited to commodity price forecasting, electricity demand forecasting, and weather forecasting [40–42].

3.3. Compare forecasts

Binary data can be evaluated using various scores, such as Accuracy and F1 scores, which rely on the concept of true/false positives and negatives. A true positive (TP) occurs when a model accurately predicts a positive outcome, while a true negative (TN) transpires when a model accurately predicts a negative outcome. Conversely, a false positive (FP) arises when a model inaccurately predicts a positive outcome, and a false negative (FN) arises when a model inaccurately predicts a negative outcome.

The Accuracy score is a commonly used performance metric in modelling and reflects the count of correct predictions divided by the total number of predictions (i.e., TP+TN)/(TP+FP+FN+TN). Despite its intuitive appeal, the accuracy score suffers from limitations, particularly when dealing with highly imbalanced classes. To overcome this limitation, complementary metrics such as the F1 score may be utilised. The F1 score is calculated as the harmonic mean of precision and recall, where precision is defined as TP/(TP+TN) and recall is defined as TP/(TP+FN). By incorporating both precision and recall, the F1 score provides a more comprehensive evaluation of model performance [43,44].

The evaluation of various models in this study involves the use of accuracy and F1 scores as performance metrics. The first model is a logistics regression model that relies solely on historical delivery scores. There subsequent models integrate both historical delivery data and Lean maturity data. The models employed in this study include logistics regression, XGBoost, MLP and a hybrid model. The methodology is summarised in Fig. 1.

4. Results

Supply chain company that was used for this study comprises of numerous teams that undergo Lean maturity audits, which encompass questions across 20 distinct sections. The results of these audits can be evaluated as binary outcomes, with each section being either passed or failed by a team. The teams' key performance measure is centred around delivery, which can be evaluated as binary outcomes each month, with the team either meeting or failing its targets.

The study specifically focused on examining the predictive capability for the next month's delivery score in 30 audited teams. Separate forecasting models were developed for each team, aiming to evaluate various approaches. The first model employed univariate logistics regression, while the second model incorporated Lean maturity assessments data into the logistics framework. The third and fourth models utilised MLP and XGBoost with Lean data as input. Lastly, a hybrid model was constructed, consisting of a multivariate logistics in the initial step, followed by the application of MLP on the logistics results and KPI lags to further enhance the forecast accuracy. The evaluation of the models' performance, including accuracy and F1 scores, are presented in Figs. 2 and 3. Score values across the 30 teams are summarised in Tables 2 and 3.

Several key observations can be drawn from the analysis. Firstly, the Multivariate logistics approach yields superior average scores compared to the Univariate approach, indicating that incorporating Lean maturity data in multivariate forecasting enhances the accuracy of KPI forecasting for the 30 teams within the selected supply chain company.

Secondly, the scores obtained from the MLP and XGBoost models are lower than those achieved through multivariate regression. This suggests that these models may overfit the data during the training process. Considering the difficulty in correctly implementing MLP and XGBoost models, it can be concluded that multivariate regression modelling is more suitable for the specific supply chain company examined in this study compared to MLP and XGBoost [45].

Lastly, the hybrid model demonstrates the best performance, aligning with the latest best practices in the forecasting domain, which emphasise the advantages of utilising hybrid models. The hybrid model demonstrated a superior accuracy score of 17 % and an improved F1 score of 13 % when compared to the univariate logistics model.

In summary, the multivariate hybrid model with Lean maturity data outperformed a univariate regression model. This study on the supply

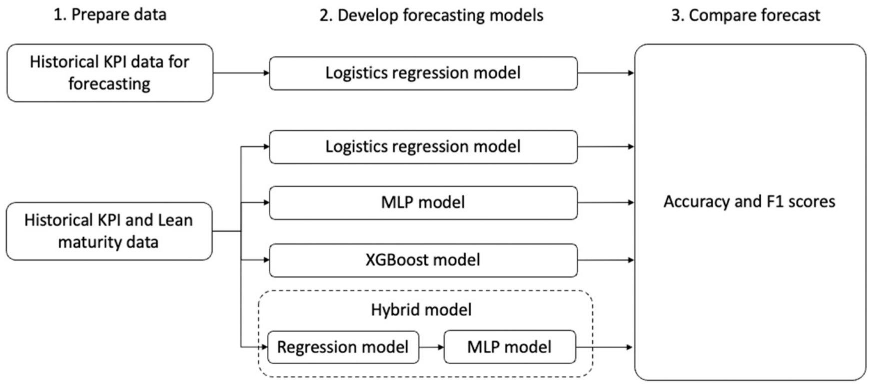

Fig. 1. Methodology summary.

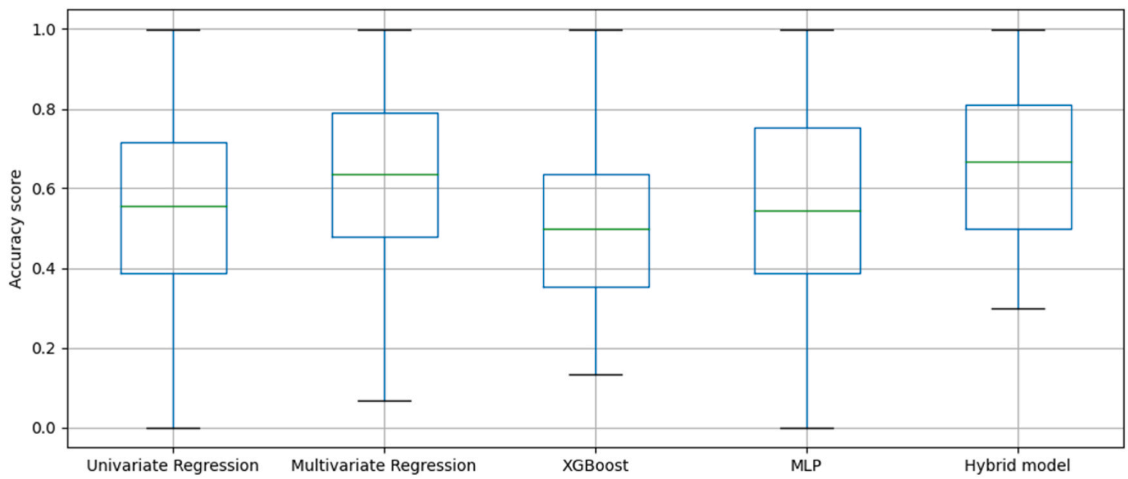

Fig. 2. Accuracy scores boxplots to forecast delivery KPI for the 30 teams in the study using 5 different models.

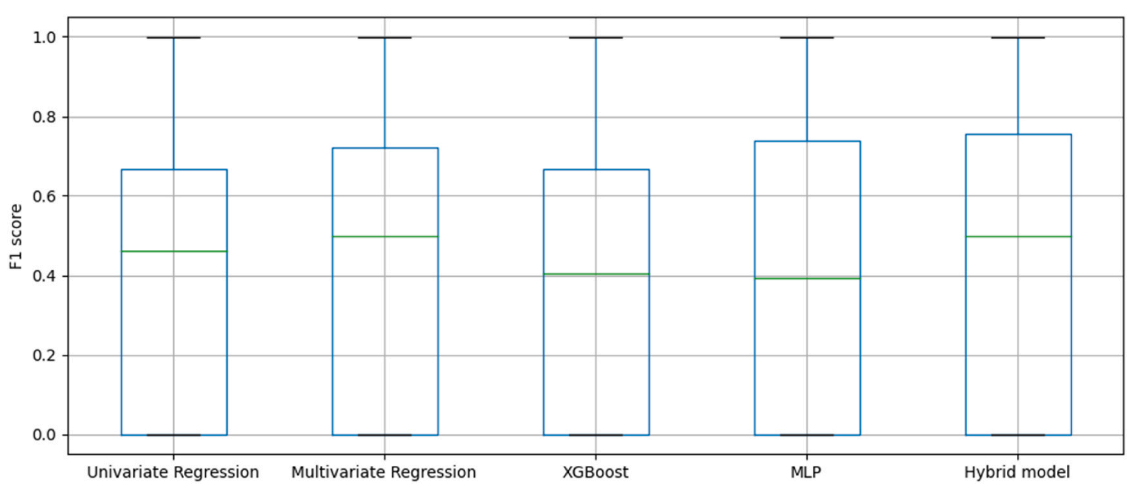

Fig. 3. F1 scores boxplots to forecast delivery KPI for the 30 teams in the study using 5 different models.

chain context confirms the benefits of the proposed methodology for improving KPI forecasting in supply chains. The incorporation of Lean maturity assessments results in enhanced forecasting accuracy, while the utilisation of hybrid models further boosts the accuracy levels.

5. Discussion

In this study we explored the concept of using Lean maturity Assessment data as a potential data source to be used in Forecasting within Predictive Analytics. The multivariate approach used in this paper captures the interdependencies and correlations between various Lean and delivery performance elements within the supply chain, enabling more accurate and robust forecasts. The findings of this study provide empirical evidence that the inclusion of Lean maturity data significantly improves the accuracy of supply chain KPI forecasts.

The contribution of this study to the advancement of the supply

Table 2
Average accuracy scores across 30 teams using different forecasting models.

Team	Univariate regression	Multivariate regression	XGBoost	MLP	Hybrid model
1	0.636	0.636	0.636	0.727	0.818
2	0.455	0.455	0.455	0.545	0.455
3	0.455	0.455	0.455	0.455	0.455
4	0.667	0.667	0.500	0.667	0.667
5	1.000	1.000	1.000	1.000	1.000
6	0.500	0.500	0.500	0.500	0.500
7	0.667	0.667	0.667	0.667	0.667
8	0.800	0.800	0.800	0.800	0.800
9	0.900	0.900	0.800	0.900	0.900
10	0.933	0.933	0.933	0.067	0.933
11	0.067	0.067	0.133	0.067	0.800
12	0.733	0.733	0.867	0.867	0.733
13	0.733	0.733	0.600	0.600	0.733
14	0.000	0.917	0.500	0.000	0.917
15	0.429	0.429	0.429	0.429	0.429
16	0.500	0.500	0.500	0.500	0.500
17	0.636	0.636	0.636	0.636	0.364
18	0.500	0.500	0.500	0.500	0.500
19	0.364	0.818	0.182	0.545	0.818
20	0.333	0.333	0.222	0.778	0.556
21	0.636	0.818	0.545	0.818	0.818
22	0.556	0.556	0.556	0.556	0.556
23	0.375	0.375	0.375	0.375	0.375
24	1.000	1.000	1.000	0.000	1.000
25	0.400	0.400	0.600	0.400	0.300
26	0.778	0.778	0.222	0.778	0.778
27	0.222	0.556	0.222	0.778	0.556
28	0.333	0.333	0.222	0.222	0.333
29	0.333	0.667	0.333	0.167	0.667
30	0.700	0.600	0.200	0.200	0.600
Average	**0.555**	**0.625**	**0.520**	**0.518**	**0.651**

Table 3
Average F1 scores across 30 teams using different forecasting models.

Team	Univariate regression	Multivariate regression	XGBoost	MLP	Hybrid model
1	0.778	0.778	0.778	0.769	0.857
2	0.625	0.625	0.625	0.545	0.400
3	0.625	0.625	0.625	0.625	0.625
4	0.800	0.800	0.500	0.800	0.800
5	1.000	1.000	1.000	1.000	1.000
6	0.667	0.667	0.667	0.000	0.667
7	0.000	0.000	0.000	0.000	0.000
8	0.000	0.000	0.000	0.000	0.000
9	0.947	0.947	0.889	0.947	0.947
10	0.000	0.000	0.000	0.125	0.000
11	0.000	0.000	0.235	0.000	0.889
12	0.333	0.333	0.000	0.000	0.333
13	0.500	0.500	0.000	0.400	0.500
14	0.000	0.000	0.000	0.000	0.000
15	0.600	0.600	0.556	0.600	0.600
16	0.667	0.667	0.667	0.667	0.667
17	0.778	0.778	0.778	0.778	0.462
18	0.667	0.667	0.667	0.667	0.667
19	0.462	0.833	0.182	0.706	0.833
20	0.500	0.500	0.000	0.875	0.714
21	0.778	0.900	0.615	0.889	0.900
22	0.000	0.000	0.000	0.000	0.000
23	0.000	0.000	0.000	0.000	0.000
24	1.000	1.000	1.000	0.000	1.000
25	0.000	0.000	0.750	0.000	0.364
26	0.000	0.000	0.364	0.000	0.000
27	0.000	0.600	0.000	0.875	0.600
28	0.250	0.000	0.364	0.000	0.000
29	0.200	0.333	0.500	0.167	0.333
30	0.400	0.000	0.333	0.333	0.000
Average	**0.419**	**0.438**	**0.403**	**0.392**	**0.472**

chain analytics field can be understood through two key aspects. Firstly, it introduces a novel and underutilised data source derived from Lean maturity assessments. By incorporating this new data source into the forecasting process, the study demonstrates the superiority of the multivariate approach over the traditional univariate approach.

Secondly, the study recognises the value of incorporating hybrid models, which are widely acknowledged as effective approaches in the field of forecasting. Hybrid models bring together the strengths of various forecasting techniques, including Logistics regression and MLP, to address the limitations of individual models. By combining different modelling approaches, hybrid models can harness the benefits offered by each technique, leading to improved accuracy and dependability in forecasting. Logistics regression plays a crucial role in highlighting the significance of specific features, enabling supply chain teams to gain insights into the importance of various Lean maturity aspects for delivery. On the other hand, MLP facilitates the identification of intricate patterns within the data, thereby enhancing the accuracy of forecasts.

The adoption of hybrid models in this study further enhances the accuracy of supply chain forecasts, as demonstrated by the outcomes obtained from the 30 participating teams. The improved accuracy, as measured by the 17% increase in the accuracy score and the 13% improvement in the F1 score, highlights the potential of hybrid models to effectively capture the complexity and dynamics of supply chain operations.

This research opens up new pathways for academic practitioners to enhance their studies in Supply Chain analytics. Its novelty is underscored by the introduction of a distinctive data source, Lean maturity assessments, and the adaptation of a hybrid forecasting model, traditionally used for categorical forecasting, to the domain of supply chain KPI forecasting. The empirical evidence derived from this study establishes a valuable benchmark for future research, providing a robust foundation for the development of advanced predictive models.

Supply chain managers gain substantial advantages, including enhanced decision-making capabilities, minimised disruptions, and valuable strategic insights into how Lean framework elements affect performance. Precise KPI forecasting empowers proactive troubleshooting, leading to heightened operational efficiency and greater resilience. For instance, Lean practitioners at Company A can directly observe the impact of Lean improvements on future performance. Simultaneously, operations managers receive timely notifications about potential delivery delays in the near future, enabling them to take proactive measures to prevent disruptions and ensure timely deliveries.

6. Conclusion

The realm of Supply Chain performance management is currently encountering significant prospects, such as the advent of Industry 4.0, the utilisation of Big Data Analytics, and the emergence of artificial intelligence. These developments have stimulated the demand for efficient solutions within the field. Consequently, the objective of this investigation is to tackle these challenges by utilising predictive analytics on lean maturity data to enhance the forecasting of supply chain KPIs. However, upon reviewing the existing literature on process improvement data, it becomes evident that there is a lack of studies that employ predictive analytics in this context. While a couple of studies have focused on TQM, the application of advanced analytics within the realm of Lean maturity remains relatively unexplored.

To bridge this research gap, a methodology was proposed that incorporates the latest trends in the forecasting domain, including multivariate forecasting and hybrid models. The methodology was applied in a study conducted on 30 teams within a large supply chain organisation to validate its effectiveness. The results revealed a substantial improvement in the accuracy score of 17% and the F1 score of 13 % for delivery KPI forecasting, highlighting the advantages of incorporating Lean maturity as a new data source and utilising the proposed hybrid model.

This study contributes to the advancement of the supply chain analytics field in two significant ways. Firstly, it introduces a novel and underutilised data source derived from Lean maturity assessments, demonstrating that the multivariate approach incorporating this new data source outperforms the traditional univariate approach. Secondly, the study embraces the adoption of hybrid models, which are recognised as best practices in the forecasting domain. These advancements have the potential to significantly enhance the accuracy of supply chain forecasts, as evidenced by the outcomes obtained from the 30 participating teams in this study.

6.1. Limitations and further research

One limitation of this study is that it focused on a single supply chain organisation to validate the proposed methodology. Although the sample size of the teams was large, extending the application of the methodology to more companies would provide a broader perspective and help uncover the benefits and limitations of the proposed forecasting approach in different contexts.

While this study primarily focused on Predictive Analytics using process improvement data, it should be viewed as a starting point for leveraging advanced analytics in process improvement maturity assessments. The next potential avenue lies in exploring prescriptive analytics. For instance, analysing the features included in our forecasting model can provide insights into the key drivers behind significant changes in the delivery KPIs. By tailoring the analysis to each team, it becomes possible to create a personalised Process Improvement journey, highlighting specific aspects of Lean that each team should prioritise. For example, one team might benefit from focusing more on VSM, while another team might need to allocate more time to 5 S implementation.

Furthermore, there is an opportunity to explore additional data sources within the process improvement domain. For instance, considering the counts of accredited Lean Six Sigma professionals, such as Yellow, Green, and Black Belts, within each team could provide valuable insights. By incorporating this information into the forecasting model, a more comprehensive understanding of the relationship between human resources and performance outcomes can be achieved.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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