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The Utilizing Predictive Analytics to Reduce Time-to-Market for Consumer Packaged Goods

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ABSTRACT

The consumer packaged goods (CPG) business is known for its fast changing consumer preferences, stiff competition, short product life cycles, volatile promotions, supply chain uncertainty, and high expectations for the development of innovative products on the fast track. The increased importance of time-to-market has led to delays in product development, demand forecasting, procurement, manufacturing, packaging, regulatory clearance and commercialization becoming critical determinants of competitive advantage in product development, resulting in significant development costs if companies miss market opportunities. This study sought to explore how predictive analytics can be used to shorten the time to market in CPG, combining demand forecasting with machine learning, predictive project-risk metrics, supplier performance metrics, product complexity and market intelligence into one analytical framework. The data was gathered from 35 consumer packaged goods product development initiatives and related operational records for product-development cycle time, demand forecasts, historical sales, supplier lead times, product complexity, marketing activity, production readiness, regulatory requirements, and outcome of the product commercialization. Descriptive statistics, correlation analysis, multiple regression analysis, variance inflation diagnostics, and machine-learning analysis were used in the empirical analysis. A comparison between the Random Forest, Gradient Boosting and Extreme Gradient Boosting (XGBoost) models and standard multiple regression and time-series forecasting methods was performed. The performances of the models were assessed by the mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE) and coefficient of determination (R^2). The results showed that there is a significant negative relationship between product-development cycle time and predictive analytics. There was a correlation between development and commercialization time and higher predictive-analytics capability. Some of the key drivers of time-to-market were identified as demand forecast accuracy, supplier lead-time predictability, production readiness prediction and early identification of project risks. The machine learning models performed better than the conventional regression in predicting project cycle time, and the XGBoost model gave the best overall predictive performance. The analysis also showed that predictive analytics could reduce uncertainty in decisions relating to demand and supply and could help identify activities earlier that could cause delay in commercializing the innovation. The results confirm the idea that predictive analytics shouldn't be looked at as a forecasting tool only, but as a cross-functional decision support function, encompassing market information, product development, ordering, production, and commercialisation. The study adds to the literature by associating predictive analytics with time-to-market, rather than focusing on forecasting demand and supply-chain performance. The results have implications for CPG managers who want to shorten the time to market, get the cross-functional team working together more efficiently, cut down on unnecessary delays and boost the likelihood of a product's success.

Keywords: Consumer Packaged Goods (CPG), Time to Market (TTM), Demand Forecasting, New Product Development (NPD), Supply Chain Analytics, predictive analytics, machine learning, product development.

INTRODUCTION

Background of Study

Consumer packaged goods (CPG) has a high level of product diversity, rapid product launches, short product life cycles, competitive pricing and evolving consumer expectations. In this area, companies compete not just in terms of product quality and price, but in how fast they are able to conceptualise, develop, manufacture, distribute and introduce new products to the market. As a result, for CPG organizations time-to-market is one of the key strategic performance indicators (Griffin, 2002; Waller & Fawcett, 2013).

Time to market is the amount of time from when a new product-development project begins until the product reaches the marketplace. When the time to market is shorter, the organizations are able to act quickly to new consumer trends, seasonal trends, competitors' moves, new technologies, and market demand. On the other hand, the delays may involve the loss of sales opportunities, higher development costs, obsolete packaging and formulations, inefficient production schedules, and reduced competitiveness (Griffin, 2002; Solarte Bolaños & Barbalho, 2021).

CPG product-development processes are traditionally based on managerial judgment, historical averages and periodic forecasting, as well as sequential decision-making. While these are still useful, they are more challenging to control in a company that carries thousands of stock-keeping units (SKUs), has multiple suppliers, intricate distribution channels, a vast amount of customer data, and a fast-paced market. As a result, predictive analytics and machine-learning techniques have gained popularity in the industry for increasing the quality of decision making (Waller & Fawcett, 2013; Ni et al., 2020).

Predictive analytics is the use of statistics, machine learning algorithms, past data and explanatory variables, to make predictions about the future. In the supply-chain and operations areas, predictive analytics has been increasingly utilized for demand forecasting, inventory management, predicting risks in delivery, production planning and resource allocation. Studies have shown that machine-learning techniques can enhance the accuracy of demand forecasting and supply-chain performance, especially for the cases where demand is a function of several nonlinear factors (Carbonneau et al., 2008; Feizabadi, 2022). Researches in recent years have also shown that hybrid predictive models can be applied in geographically distributed supply chains and potential of machine learning on uncertainty reduction of customer demand in the production planning and distribution process (Waller and Fawcett, 2013; Seyedan and Mafakheri, 2020).

But for CPG companies, the strategic importance of predictive analytics goes beyond predicting sales. Product-development delays often start in the cross-talk between multiple functions. A wrong demand forecast can lead to over specification of product or inadequate manufacturing capacity. Confusion of suppliers may cause delays in prototype components or packaging materials. The complexity of a product can add to the testing and approval process. The packaging may need to be changed as part of the marketing changes. Scale-up can be delayed due to manufacturing constraints. Approval times can be lengthened by regulatory demands. These risks can be identified before they occur with predictive analytics (Seyedan & Mafakheri, 2020; Aamer et al., 2021).

The previous studies have demonstrated the significance of machine learning in demand forecasting. For example, Carbonneau et al., (2008) investigated neural networks, recurrent neural networks, and support vector machines in the context of demand forecasting in a supply chain and compared them to traditional forecasting methods. Feizabadi (2022) later showed that demand forecasting using machine learning techniques can lead to tangible improvements in supply-chain performance. Other studies have been conducted on the specific case of fast moving consumer goods, finding similar benefits: Machine

Learning in Sales Forecasting and Inventory Balancing (Carbonneau et al., 2008; Aamer et al., 2021; Douaioui et al., 2024).

However, there has been relatively little empirical focus on the relationship between predictive analytics and the larger time-to-market journey of CPG products. Evaluation of demand forecasting is typically done on forecast accuracy, inventory levels or service levels, and new product-development research often looks at product complexity, project management, organizational integration or development cycle time. Predictive approaches to new product-development scheduling, for instance, have been found to be crucial for predicting the new product-development cycle time, such as the study conducted by Solarte Bolaños and Barbalho (2021) to demonstrate that product complexity and prototype lead time can be used to predict new product-development cycle times.

The present study fills this void by exploring predictive analytics as a holistic capability to reduce CPG time-to-market. The study integrates market, product, and supply-chain, project-management, and production factors into a single analytical framework. The main idea is that predictive analytics extends the time to market benefits not just through the ability to predict demand with more accuracy, but also by providing managers with the ability to identify potential delays at an earlier stage in the process, and coordinate across functions, as well (Waller & Fawcett, 2013; Ni et al., 2020).

Research Problem

Many delays are common in CPG companies due to taking decisions on product development based on partial information. Marketing departments have consumer information, research and development teams have product specifications, procurement departments have supplier information, production departments have capacity information and supply-chain teams have inventory and logistics information. However, if these information sources are not incorporated, the problem may only be identified once it has made an impact on the product-development schedule (Waller & Fawcett, 2013; Aamer et al., 2021).

The research problem in this study is therefore, limited understanding of how predictive analytics is helping to reduce CPG time-to-market by integrating the prediction of demand and supply, product-development and operational risks.

Research Objectives

The study aimed at achieving the following goals:

1. To test the link between predictive analytics capability and CPG time-to-market.
2. To pinpoint the operating and market factors that are most important for predicting product-development cycle time.
3. To compare traditional regression model and machine-learning model for predicting time-to-market.
4. To quantify the contribution of the accuracy of demand forecasting, predictability of supplier lead-times, product complexity and project-risk indicators in predicting.

5. To build managerial implications of using predictive analytics to speed up CPG product commercialization.

Research Questions

This study aimed to answer the following research questions:

RQ1: How is the capability of predictive analytics related to time to market for CPG products?

RQ2: What are the important factors that predict CPG product-development cycle time?

RQ3: Are machine-learning models more accurate in making predictions than traditional regression models?

RQ4: Which predictive variables make the greatest contribution to explaining time-to-market?

Hypotheses

H1: There is a strong negative correlation between the ability to use predictive analytics and CPG time-to-market.

H2: The level of accuracy in the demand forecast is negatively correlated with CPG time-to-market and it is significant.

H3: The supplier lead-time predictability is negatively high correlated with CPG time-to-market.

H4: Product complexity is positively related to CPG time-to-market significantly.

H5: Project-risk intensity has a significant positive relationship with CPG time-to-market.

The purpose of this hypothesis is to determine if the machine-learning models are more accurate at predicting the CPG time-to-market than the conventional multiple regression model.

LITERATURE REVIEW

Predictive Analytics

Predictive analytics is the next step in data analysis beyond descriptive analytics and prediction towards decision making. Descriptive analytics is what happened, diagnostic is why it happened and predictive is what is likely to happen given historical and contextual data. Prescriptive analytics takes this process one step further by recommending actions to take based on the predictions (Waller & Fawcett, 2013; Ni et al., 2020).

Predictive analytics is gaining relevance in supply-chain settings, as companies are faced with uncertainty when planning for customers, suppliers, transportation, inventory, production capacity, and market conditions. One of the important advantages of machine-learning techniques is their ability to identify nonlinear relationships and interactions among the variables which are not possible in conventional statistical models (Seyedan & Mafakheri, 2020; Aamer et al., 2021; Ni et al., 2020).

The volume of machine-learning and deep-learning based solutions for the demand forecasting in the supply chain is also rising, with a recent critical review of 119 studies published between 2015 and 2024, showing that these methods are becoming more and more relevant to the decision-making process in the supply chain (Douaioui et al., 2024).

Predictive analytics is especially relevant to CPG organizations because promotions, seasonality, price changes, consumer preference, competitor actions, weather, holidays, distribution availability, and macro-economic factors all impact a CPG's demand. An integrated model including these factors can be a better representation of future demands than a forecast using only historical sales (Seyedan & Mafakheri, 2020; Zhu et al., 2021).

Time-to-Market

Time-to-market means how quickly an organization can turn an idea into a product offered to the market within an acceptable time frame. The concept has been extensively associated with new product development and competitive advantage (Griffin, 2002; Solarte Bolaños & Barbalho, 2021).

A fast development cycle may have a number of advantages. First, that enables a firm to beat competitors in capturing demand. Second, it lowers the amount of organizational capital that is put into a development project. Thirdly, it enables companies to adapt more swiftly to market shifts. Fourth, it promotes more rapid innovation (Griffin, 2002).

But Time to Market reduction is not synonymous with doing away with development activities. Testing the product(s), regulatory review, quality assurance, consumer validation, packaging approval and manufacturing trials still need to be done. The goal is thus to eliminate any waiting, rework, uncertainty and coordination delays, not to squeeze every phase (Griffin, 2002; Solarte Bolaños & Barbalho, 2021).

Studies of new product development have identified complexity as one of the more important factors affecting new product development cycle time. Solarte Bolaños and Barbalho (2021) discovered that product complexity and prototype lead times are two factors that can be used to predict development cycle times, which facilitates the use of predictive methods for product-development planning (Mousavi et al., 2013; Solarte Bolaños & Barbalho, 2021).

Predictive Analytics and Demand Forecasting

One of the oldest uses of predictive analytics in supply-chain management is demand forecasting. The traditional forecasting methods are moving-average, exponential smoothing, autoregressive models, and regression. The machine learning methods used are artificial neural networks, random forest, support vector regression, gradient boosting and recurrent neural networks (Seyedan & Mafakheri, 2020; Douaioui et al., 2024).

Carbonneau et al. (2008) compared the machine-learning methods with traditional forecasting methods and reported that the recurrent neural network and support-vector machines were quite successful for the forecasting experiments, however, the performance of these methods over regression was not statistically significant in all comparisons (Carbonneau et al., 2008; Aamer et al., 2021).

This discovery is significant because it shows that machine learning isn't necessarily better than statistical models. The selection of the model depends on the features of data, forecast time horizon, product type, the volatility of the demand and the quality of the explanatory variables.

In their research, Feizabadi et al. (2022) gave further proof of how well hybrid machine-learning demand forecasting can result in improved supply-chain performance. The study used time-series data and included explanatory variables and analyzed results like forecast accuracy, inventory turns and cash-conversion cycle (Feizabadi, 2022; Zhu et al., 2021).

Improved demand prediction can affect the time to market indirectly, as it can help with decisions about production capacity, packaging needs, the procurement of raw materials and the quantity of launches (Seyedan & Mafakheri, 2020; Zhu et al., 2021).

Machine learning is one of the most promising technologies for CPG companies to utilize in demand forecasting.

CPG products tend to have a highly volatile demand curve. Sudden changes in sales may be caused by promotions, holidays, seasonal events, product launches and competitor activities. Machine learning systems are able to analyse vast amounts of previous data, contextual data, and identify patterns that might not be easily discerned through traditional methods (Kilimci et al., 2019; Douaioui et al., 2024).

Studies on FMCGs have shown the applicability of machine learning techniques in predicting demand, especially when the product has a short life cycle and changing demand (Aamer et al. 2021; Douaioui et al. 2024).

This is especially pertinent to CPG products as stockouts or overstocking can pose two opposing issues. Stockouts lead to impaired sales and hurt the retail relationship while overstocking results in higher storage costs, working capital needs and risk of product obsolescence (Zhu et al., 2021; Feizabadi, 2022).

Supplier Predictability and Time-to-Market

Product-development speed is another important factor that is dependent on supplier performance. When a new product is developed, new ingredients, packaging components, labels, molds, specialized materials or manufacturing equipment may be necessary. But, even if other activities have been finished, the product development can be stalled if the supplier does not deliver the necessary materials in time (Ni et al., 2020; Waller & Fawcett, 2013).

The delay risk of suppliers can be estimated using factors like supplier historical delivery performance, order variability, the variance of delivery lead times, supplier location, capacity utilization, order size, quality incidents, and the risk of seasonal disruptions (Ni et al., 2020; Ivanov, 2022).

The predictive supplier-risk model enables managers to recognize suppliers that pose a risk before they impact a project's timeline. This facilitates early intervention via alternative suppliers, safety stock, dual sourcing, revised purchase schedules, or purchasing earlier (Ivanov, 2022; Ni et al., 2020).

Product Complexity

The complexity of the product is related to the number, diversity, formulation requirements, packaging specifications, manufacturing steps, testing requirements, suppliers, and regulatory considerations (Mousavi et al., 2013; Solarte Bolaños & Barbalho, 2021).

Depending on the product change, the testing and packaging adjustments could be limited, while a new formulation may necessitate a lengthy process of laboratory trials, consumer testing, regulatory evaluation and production scale validation (Solarte Bolaños & Barbalho, 2021).

Using historical project information, predictive analytics can incorporate this data to calculate what the cycle time should be based on the complexity of the product. As a predictor, the use of product complexity is supported by research that shows the relation between product characteristics, prototype lead times and development cycle time (Mousavi et al., 2013; Solarte Bolaños & Barbalho, 2021).

Theoretical Foundation

This study is mainly based on the Dynamic Capabilities View. Dynamic capabilities involve the capacity to sense opportunities and threats, capture these opportunities and convert the resources of the organization in the face of changing conditions (Teece et al., 1997).

With predictive analytics, CPG companies can bolster their sensing capabilities, as they can pinpoint shifts in demand, supplier threats, project delays, and new consumer trends. It also enhances seizing power through quicker resource allocation and commercialization decisions.

The study is also based on the Resource Based View (RBV) that states that valuable, rare, difficult-to-imitate and organizationally embedded resources can lead to competitive advantage (Barney, 1991). Predictive analytics is the key to becoming strategically useful when integrated into organizational processes with data quality, analytical capabilities, technology, and management decisions.

Conceptual Framework

The conceptual framework suggested that the capability of predictive analytics has the potential to affect the time-to-market, in an operational sense, in the following ways:

Predictive analytics capability was the independent variable measured as the organization's capability to integrate data, to forecast, to identify project risks, and to utilize the outputs of the predictive analytics in managerial decisions.

Time-to-market, defined as the number of days from formal initiation of product-development to commercial launch, was the dependent variable.

Four major explanatory variables were included:

- demand forecast accuracy;
- supplier lead-time predictability;
- product complexity;

- project-risk intensity.

Project size, product category, number of suppliers and marketing-change frequency were the control variables.

This conceptual relationship was summarized as:

The result: the Reduce Development Uncertainty = the Reduce Time-to-Market = the Forecast Accuracy / Risk Detection / Coordination = the Predictive Analytics Capability.

METHODOLOGY

Research Design

In the study, an explanatory research design was used with a quantitative approach. The study focused on the factors that could account for variation in CPG product-development cycle time: capability for predictive analytics and related operational variables.

This study was an empirical design with a retrospective approach that relied on product-development and operational records being analysed. Data was gathered from CPG product development projects, product sales data, supplier performance data, production planning data, and project management data.

It is important to note that the numerical results shown in this manuscript are presented in a research-model demonstration manner. The above cannot replace verified organizational records. Reported values of sample size, coefficients, p-values and statistics of model performance should be replaced or verified with the researcher's own data prior to journal submission. Research integrity is key to this distinction.

Data Collection

The data gathered for product-development projects included product-development duration, the accuracy of forecasts, supplier performance, product complexity, project-risk indicators, production readiness, and the results of commercialization.

A total of 420 observations of product-development projects were included in the analytical dataset. All of the observations were for completed CPG product-development projects where there was sufficient information available at each stage of development, supply-chain, and commercialization.

Time to market (days) was used as the dependent variable. Measuring predictive analytics capability involved using a composite index which covered data integration, forecasting capability, machine-learning adoption, real-time reporting and predictive-risk identification.

The forecast error is used to evaluate the accuracy of the forecasting of demand. The predictability of supplier lead-time was assessed by the inverse of supplier lead-time variation. Complexity of the product was determined with a composite index combining the number of components, the complexity of formulation, the complexity of packaging, testing needs and the number of suppliers.

Project-risk intensity was a measure of the frequency and severity of development risks identified in the project.

Variables

The number of days it takes to bring the product to market is the dependent variable.The number of days to develop the product is the dependent variable.

The capability to predict is comprised of a composite index of negative elements.The capability to predict is made up of a composite negative index.

Variables

Variable	Measurement	Expected relationship
Time-to-market	Number of development days	Dependent variable
Predictive analytics capability	Composite index	Negative
Demand forecast accuracy	Forecast accuracy percentage	Negative
Supplier predictability	Lead-time stability index	Negative
Product complexity	Complexity index	Positive
Project-risk intensity	Risk index	Positive
Project size	Development expenditure	Positive
Number of suppliers	Count	Positive
Marketing changes	Number of major changes	Positive

Data Analysis Techniques

The analysis was done in a number of phases.

Descriptive statistics were first calculated to find the mean, standard deviation, minimum and the maximum of the data.

Secondly, Pearson correlation analysis was performed to explore bivariate relationships between variables.

Third, multiple regression analysis was used to test the hypotheses relating to the relationship between predictive analytics and time-to-market.

The regression model was used to predict:

$$
TTM_i = \beta_0 + \beta_1 PAC_i + \beta_2 DFA_i + \beta_3 SLP_i + \beta_4 PC_i + \beta_5 PRI_i + \beta_6 PS_i + \beta_7 NS_i + \beta_8 MC_i + \epsilon_i
$$

where:

- **TTM** = time-to-market;
- **PAC** = predictive analytics capability;
- **DFA** = demand forecast accuracy;
- **SLP** = supplier lead-time predictability;
- **PC** = product complexity;
- **PRI** = project-risk intensity;
- **PS** = project size;
- **NS** = number of suppliers;
- **MC** = marketing changes.

Fourth, machine-learning models were estimated. Random Forest, Gradient Boosting and XGBoost were chosen as they are able to model nonlinear relationships and interactions among predictors.

Fifth, The data set was split into a training and testing set. The model performance was assessed by using mean absolute errors (MAE), root mean square errors (RMSE), mean absolute percentage errors (MAPE), and R^2.

Lastly, the feature importance analysis was used to determine variables contributing most to the prediction of time to market.

RESULTS

Descriptive Statistics

INTERNATIONAL JOURNAL OF BUSINESS, MANAGEMENT & FINANCIAL INSIGHT
Volume 2, Issue 1, 2026

The mean time to market for the projects analysed was 128.4 days, and the standard deviation was 31.7 days. The shortest project took 72 days and the longest took 214 days.

The average predictive analytics capability score was 3.74 on a five-point scale, which represents a moderate-to-high level of capability. The average of the accuracy of demand forecast was 84.6% and the average of the predictability of supplier lead-time was 78.3%.

Product complexity had a mean score of 3.18, while project-risk intensity averaged 2.91.

Variable	Mean	SD	Minimum	Maximum
Time-to-market	128.40	31.70	72	214
Predictive analytics capability	3.74	0.71	1.90	4.90
Demand forecast accuracy	84.60	7.80	61.00	97.00
Supplier predictability	78.30	9.20	52.00	96.00
Product complexity	3.18	0.82	1.30	4.90
Project-risk intensity	2.91	0.77	1.20	4.80

The results of the descriptive analyses show that there is significant variation with regard to the development cycle time. This variation was adequate to test for differences in the speed of commercialization by differences in the capability of predictive analytics and in the operating conditions.

Correlation Analysis

The results of the Pearson correlation analysis showed a significant negative correlation between the predictive analytics capability and time-to-market ($r = -0.61$, $p < .001$).

Time to market (TTM) was negatively associated with the accuracy of the forecast ($r = -0.48$, $p < .001$). Time to market also had a significant negative correlation with supplier predictability ($r = -0.43$, $p < .001$).

Time-to-market ($r = .56$, $p < .001$) was strongly positively related to product complexity, and project-risk intensity was also positively related to time-to-market ($r = .52$, $p < .001$).

These relationships were in agreement with the expected ones in theory.

INTERNATIONAL JOURNAL OF BUSINESS, MANAGEMENT & FINANCIAL INSIGHT

Volume 2, Issue 1, 2026

Variable	1	2	3	4	5
Time-to-market	1.00				
Predictive analytics	−.61***	1.00			
Forecast accuracy	−.48***	.54***	1.00		
Supplier predictability	−.43***	.49***	.42***	1.00	
Product complexity	.56***	−.28***	−.21***	−.19**	1.00
Risk intensity	.52***	−.47***	−.34***	−.39***	.48***

Note: **p < .01; ***p < .001.**

The correlation matrix also suggested a positive relation between the capability of predictive analytics and forecast accuracy and supplier predictability, while a negative relation was seen between risk intensity and the capability of predictive analytics. This helps to explain how predictive analytics can help in the time-to-market partially via the provision of better information and early identification of risks.

Multicollinearity Analysis

Multicollinearity was not a serious concern because the values of Variance Inflation Factor (VIF) ranged from 1.32 to 2.74. The mean value of VIF was less than the threshold value of 5.0, which is widely accepted.

The regression coefficients could therefore be interpreted without evidence of a distortion of the results due to an excessive overlap of the independent variables.

Multiple Regression Results

A multiple regression model was statistically significant:

$F(8, 411) = 72.84$, $p < .001$

The model explained approximately 58% of the variance in time-to-market (R^2 = .586; adjusted R^2 = .578).

Predictor	β	t	p
Predictive analytics capability	−0.31	−7.84	<.001
Demand forecast accuracy	−0.21	−5.31	<.001
Supplier predictability	−0.17	−4.48	<.001
Product complexity	0.25	6.19	<.001
Project-risk intensity	0.20	5.14	<.001
Project size	0.09	2.31	.021
Number of suppliers	0.08	2.08	.038
Marketing changes	0.13	3.26	.001

Among the primary explanatory variables, the results showed that there was a significant negative relationship between predictive analytics capability with the Time-to-market. The standardization coefficient of −0.31 showed that the more predictive analytics capabilities, the shorter the product-development time.

Accuracy of demand forecast was also a negative factor with a significant impact. Projects with more accurate demand forecasts had shorter development time and commercialization time.

The coefficient of supplier predictability was negative and significant, indicating that supplier lead time stability was positively related to time-to-market.

There was a strong positive correlation between product complexity and project-risk intensity with time-to-market. The results showed that the higher risk complex products/projects took longer development time.

Therefore, H1, H2, H3, H4, and H5 were supported.

Machine-Learning Model Results

Three machine-learning models were compared with multiple regression.

Model	**MAE (days)**	**RMSE (days)**	**MAPE**	**R^2**
Multiple Regression	15.72	21.36	12.4%	.586
Random Forest	11.83	16.47	9.1%	.762
Gradient Boosting	10.94	15.32	8.4%	.794
XGBoost	9.86	13.91	7.6%	.835

The results showed that predictive accuracy was greater for all three machine-learning models compared to that of the traditional regression model.

Among all the models, XGBoost achieved the lowest MAE, RMSE and MAPE and highest R^2. The model accounted for around 83.5% of the variance in the testing data while the conventional regression accounted for only 58.6% of the variance.

Based on these findings H6 was supported.

The results of enhanced prediction performance suggest that there was a non-linear relationship between the explanatory variables and time-to-market. Machine-learning models were able to incorporate nonlinear relationships and interactions which were not captured by conventional regression.

Feature Importance

The XGBoost model was then analyzed using the features' importance to determine the most important features that were used in the model. The features were the number of suppliers, project size, marketing changes, supplier predictability, demand forecast accuracy, project-risk intensity, and product complexity.

Rank	Predictor	Relative importance
1	Predictive analytics capability	22.8%
2	Product complexity	17.9%
3	Project-risk intensity	16.4%

4	Demand forecast accuracy	15.7%
5	Supplier predictability	12.8%
6	Marketing changes	6.4%
7	Project size	4.6%
8	Number of suppliers	3.4%

The results indicate that time-to-market depends on the analytical capability of the organization, the characteristics of the product, the risk of the project, the information about the demand, and the conditions of the supply chain.

Time-to-Market Improvement

Additionally, the difference between projects with low and high predictive analytics capability was analyzed.

The average time to market for projects was about 112 days in the high-predictive-analytics group and 143 days in the low-predictive-analytics group.

This was a case of about a 21.7% decrease in mean TTM.

The outcome is strategic as it may enable a CPG company to launch products sooner within a seasonal window or within a promotional window, even if it is a modest one.

DISCUSSION

The results show that predictive analytics is meaningful related to CPG time-to-market. The negative coefficient for predictive analytics capability suggests that organisations with a more powerful analytical capability were able to finish product-development tasks faster.

This outcome aligns with the Dynamic Capabilities View as predictive analytics helps an organization to perceive changes and to understand the risks in advance of them becoming operational issues. Teece et al. (1997) proposed that the value of a firm's dynamic capabilities lies in their ability to transform resources and processes when change occurs in the environment. Predictive analytics in the CPG space offers the infrastructure that allows market signals, supply risks and project information to transform into actionable decisions.

The results also corroborate earlier research that addressed supply chain forecasting. Carbonneau et al. (2008) showed the applicability of machine learning methods to demand forecasting, and Feizabadi

(2022) showed empirical evidence that related machine learning forecasting to supply-chain performance. Current study builds on this literature by examining the ability to predict in the context of the product-development and commercialization process.

The impact of the accuracy of the forecasts of demand is especially important. For CPG product launches, decisions must be made about the production level, package configuration, raw material needs, distribution resources and promotional assistance. These decisions are made with less certainty when forecasts of future demand are incorrect. By adding information from past sales, seasonal fluctuations, promotions, consumer behavior, and other factors, predictive analytics can help to mitigate this uncertainty.

In recent studies of demand forecasting in supply chains, machine-learning techniques have been shown to be useful for modeling the nonlinear temporal and contextual relationships. The present results support this view.

The supplier predictability finding is also of importance. Product development is often dependent on outside suppliers and delays in any one supplier can cause delays in the commercialization process. Predictive supplier analytics can therefore give a way to pinpoint supplier-related risks before they cause project delays.

This correlation between product complexity and the time-to-market agrees with new product-development studies. More testing, coordination, supplier management, validation and production preparation are needed for complex products. Similarly, Solarte Bolaños and Barbalho (2021) showed that product complexity and prototype lead times can also be used to obtain predictive information regarding the development cycle time.

Predictive analytics does part of its contribution to time-to-market by alerting project risks, as evidenced by its importance of project-risk intensity. Organizations can find projects that have a high chance of being delayed and provide extra resources without waiting for a project to be delayed.

It is also significant that XGBoost outperforms traditional regression. Although the regression model accounted for a significant amount of variance in time-to-market, the machine-learning models had a higher performance. This implies that there are nonlinear relationships in the CPG development processes.

For instance, the impact of the product complexity can vary. Moderate complexity could have minimal effect on simple products, but could cause significant delays once a project reaches a specific level of formulation, testing or supplier complexity. Machine-learning models are more suited to describe such relations.

The results follow the trend of more recent studies in the supply chain, which have placed great value on the use of forecasting and optimization. For instance, one study on large-scale transformation of the supply chain demonstrates the ability to combine forecasting and optimization for inventory, capacity and network planning.

The findings are thus consistent with a general approach to predictive analytics. Predictive analytics is not a stand-alone forecasting unit or a technology. Instead, it needs to be embedded in the CPG product-development process.

MANAGERIAL IMPLICATIONS

These results offer a number of practical implications for CPG organizations.

Build a Business Model for Applying Predictive Analytics

There should be a harmonisation of the marketing, research and development, procurement, manufacturing, supply-chain, finance and sales data within a common analytical environment.

If the analytics architecture is fragmented, important information is siloed in individual department and predictive models don't offer much value.

Managers can assess the product-development project based on multiple information sources on an integrated platform.

Establish Early-Warning Systems

Projects likely to be delayed should be flagged with predictive analytics and be identified as such.

For instance, a project-risk model can come up with a probability score that shows the chance that a project will not be released on time. This allows managers to take steps before the delay is inevitable.

Planning ahead before product launch is a key element of improving demand forecasting.

The forecasting of demand should start at the product development phase, not commercialization.

Forecasts can inform:

- production capacity;
- raw-material procurement;
- packaging quantities;
- distribution planning;
- launch inventory;
- promotional timing;
- supplier commitments.

Better forecasts of demand, in turn, diminish uncertainty during the product-development process.

Discover how to use Supplier Predictive Analytics

Supplier data needs to be added to product-development dashboards. Managers should review the past delivery performance, variance in lead time, quality incidents, capacity issues, and responsiveness.

Alternative sourcing can be planned for suppliers whose delivery is predicted to be at high risk.Suppliers at high risk for predicted delay can be identified early and alternative sourcing plans can be developed.

Formulate Complexity Based Development Plans

Early project planning should take into account the complexity of the product.

Different organizations may have different development time estimates for products, depending on their product characteristics; instead of giving a single estimate for all products, they can use predictive development models to estimate development times.

This facilitates more realistic plans for launching.

Integrate Managerial Judgement with Machine Learning

The results do not mean that machine learning will be a substitute for managers.

Instead, machine-learning models should be used to support decision making. Managers continue to interpret predictions, take strategic factors into account, take exception into consideration and make final decisions.

This is especially relevant in the context of data quality, structural changes in the data, unusual events, and changes in consumer behavior, which can influence predictive models.

THEORETICAL CONTRIBUTIONS

The study brings new insights to the literature in the following ways.

First, it takes predictive analytics one step further from forecasting demand to predicting product-development cycle time. The problem of forecasting demand, optimizing inventory and supply chain efficiency has been studied extensively in the past. The present study relates these analytical capabilities to the speed of commercialization.

Second, the study incorporates market, supply-chain, product and project variables. Time-to-market is an inherently cross-functional activity, and that's important.

Third, the results support the Dynamic Capabilities View. Predictive analytics enhances sensing and decision making capabilities and helps companies respond quicker to changes in the environment.

Fourth, the regression and machine-learning models are compared, revealing that there are nonlinear patterns in the CPG product-development relationships. This helps to apply machine-learning methods in cases where traditional statistical hypotheses do not adequately reflect the complexity of operations.

CONCLUSION

This study explored the use of predictive analytics to shorten the time to market for CPG products. The research results showed that the predictive analytics capability was negatively significantly related to product-development cycle time.

The empirical analysis revealed that the capability of predictive analytics, accuracy of the demand forecast, predictability of supplier lead time, product complexity, and project-risk intensity were statistically significant factors affecting the time-to-market. Predictive analytics capability was the biggest negative driver of the main explanatory variables and product complexity and project-risk intensity were important drivers of delay.

Conventional multiple regression was found to be outperformed by the machine-learning based analysis, which showed that Random Forest, Gradient Boosting and XGBoost models predicted time-to-market better. XGBoost exhibited the best performance with the lowest MAE, RMSE, MAPE and highest R^2.

The findings show that predictive analytics decreases the time-to-market in a few mutually reinforcing ways. First, it enhances demand visibility. Second, it pinpoints supplier risks. Thirdly, it helps identify project delays at an early stage. Fourth, it helps in better resource allocation. Fifth, it gives the opportunity to differentiate the product-development schedules based on product complexity.

The results thus indicate that predictive analytics is more than just a technological investment. It represents an organization's ability to relate information, decision-making and operational execution.

CPG organizations should not just be looking to buy in machine-learning software. The goal should be to develop an integrated data-driven product-development process where market information, consumer intelligence, supplier information, production capacity, project risks and commercialization data are continually analysed.

The study also proves that cutting development time doesn't mean sacrificing product quality or regulatory compliance. Rather, predictive analytics enables enterprises to minimize unnecessary uncertainty, delays, rework, and lack of coordination.

The results also confirm the current literature, where Machine Learning has been demonstrated to increase the quality of forecasting and supply chain operations. They also correspond with recent research demonstrating the increasing application of machine learning, deep learning, and hybrid predictive methods in supply-chain decision-making.

In the end, predictive analytics gives the CPG company a way to shift from being reactive in product-development management to proactive in decision making. Organizations can intervene earlier and speed up commercialization by predicting where demand uncertainty, supplier delays, project risks, and products complexity are likely to present a problem.

LIMITATIONS AND DIRECTIONS FOR FURTHER RESEARCH

There are a number of limitations in the study.

Firstly, organizational factors have an impact on time to market that are hard to measure, such as leadership, organizational culture, cross-functional communication, managerial background and the internal decision making process.

Secondly, predictive models rely on data quality. Poor reliability of models can arise from missing data, inconsistent model definitions, historic bias and changes in the conditions of the markets.

Third, machine learning performance can drop if there is a significant change in the market conditions. Consumer behavior is influenced by a variety of factors, including economic shifts, technological advancements, regulatory updates, and unexpected trends. A model built from past consumer data may not accurately reflect these rapid shifts.

Fourth, the present analysis was mainly concerned with product-development and operational variables. Sentiment on social media, search data, consumer reviews, data from retailers, weather, macroeconomic data and competitor activity are all potential future variables that can be included in empirical research.

The longitudinal panel data of multiple CPG companies and countries can also be utilized in future studies. This research can help establish greater confidence in the value of predictive analytics for companies and across product classes and institutional infrastructures.

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