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Adaptive Product Growth Models Powered by Predictive Analytics and Organization Risk Signals

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Abstract: *Traditional product growth models rely on retrospective data and fixed assumptions, which are increasingly inadequate under today's volatile business conditions. The study builds an adaptive growth modeling framework combining real time predictive analytics and multidimensional organizational risk signals to improve the quality of the forecasts and strategic responsiveness. The proposed approach employs a hybrid framework integrating machine learning algorithms–(Random Forest, XGBoost, and Long Short-Term Memory network) and dynamic risk evaluation procedures based on finance, operation, and market indicators. We have conducted 847 product launches in the sphere of technology, consumer goods, or financial services in the scope of 5 years of our empirical analysis. Findings indicate that the adaptive model achieves a 34% improvement in mean absolute percentage error compared with classical Bass diffusion models 22 percent of lessening than individual machine learning strategies. Moreover, the model allows the integration of organizational risk signals, which allows self-adjustment of forecasts with 87 percent accuracy in the season of market turbulence. The feature importance analysis shows that operational efficiency measures and competitive intensity measures have the most significant role in prediction refinement. The framework provides practitioners with a powerful decision-supporting framework in lifecycle management of products and also contributes to theoretical knowledge of how risk-aware adaptive systems can radically transform the growth forecasting approaches in applied computational science.*

Keywords: *Machine learning, XGBoost, Organizational risk, Financial, Operational.*

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1.0 Introduction

Product growth dynamics have long attracted the attention of researchers and practitioners; however, accurate prediction of product adoption trajectories remains a persistent challenge. Classical frameworks such as the Bass diffusion model (Bass, 1969) and logistic growth curves have been used to offer a starting point but they share a significant failure; all of them assume constant environmental conditions and constant parameter estimates. In practice, products are subject to turbulent ecosystems, in which the taste of consumers changes suddenly, competitors introduce disruptive innovation, and organizational capabilities are subject to change without warning. Take the example of rapid market expansion in 2013-2019- a trend that had not been seen in terms of early exponential gains when market saturation came in way earlier than expected (Canhoto & Arp, 2017). These failures emphasize the inefficiency of models that are not flexible and are not able to adjust to new risks and changing market conditions. These observations highlight the need for adaptive forecasting frameworks capable of responding to rapidly changing organizational and market conditions.

The emergence of big data and advances in computational capabilities have triggered a paradigm shift in forecasting methodologies. Machine learning algorithms that drive predictive analytics have now allowed organizations to process large volumes of real-time data and detect the faintest patterns that tell-tale statistical techniques fail to detect (Shmueli & Koppius, 2011; Samakinde & Arohunmolase, 2024). These methods have proven to be exceptionally successful across such areas as demand forecasting (Fildes et al., 2022) and customer churn prediction (Coussement and De Bock, 2013), but little has been done in using them to model product growth. Majority of the available studies perceive predictive analytics and growth modeling as distinct efforts as opposed to combining them into coherent systems that exploit their complementary advantages. Consequently, a unified framework integrating predictive analytics with growth theory remains insufficiently explored.

At the same time, the identification of organizational risk as a significant factor in product performance has gained significant attention. Financial distress indicators, operational inefficiencies, or competitive threats are risk signals that have a significant impact on the developmental path of a product, but they are not developed systematically in most modeling models (Hillson and Murray-Webster, 2017). A startup company with a new product may have high initial adoption, but when the organization experiences liquidity crisis or exit of key employees, the growth may happen abruptly irrespective of the merits of the product. The disruptions in the supply chain in 2020-2021 made it very clear that even the most promising product release can go off-track because of the organizational and systemic risks (Sharma et al., 2020; Sudaryana et al., 2024). Although this is a fact, majority of growth models view the organization as a black box, and only look at the market side dynamics without considering internal weaknesses that influence the outcome. Despite growing recognition of organizational risk factors, their systematic incorporation into quantitative growth forecasting models remains limited. Existing studies therefore reveal three major limitations: (i) classical growth models assume static environments, (ii) machine learning approaches often lack theoretical grounding, and (iii) organizational risk signals are rarely integrated into forecasting systems. Addressing these limitations requires an adaptive framework capable of combining theoretical structure with real-time data-driven learning (Sanni, 2023; Ndibe, 2024; Sanni, 2024).

To fill these related gaps, this study presents a modeling framework on adaptive product growth that integrates predictive analytics with risk indicators in an organization. We are driven by the fact that predicting correctly is not only a matter of having complex algorithms; but also dynamic processes that will continuously adjust the predictions as the risk profile changes. We are no longer operating on the basis of the parameter estimation which is present in the traditional models but we are applying feedback loop where the system gets to learn new data and thus modify the growth projections. Such a dynamism is vital in the modern world of business where the lifetime of strategic assumptions has been greatly reduced.

The primary aim of this study is to develop and empirically validate an adaptive product growth framework integrating machine learning with multidimensional organizational risk signals.

Specifically, the study seeks to:

(i) Develop a hybrid adaptive growth forecasting model combining classical diffusion theory and machine learning algorithms.
(ii) Examine the influence of financial, operational, market, and competitive risk signals on prediction accuracy.
(iii) Compare the performance of hybrid, classical, and standalone machine learning models.
(iv) Evaluate model adaptability under market shocks across industries

In particular, we would like to determine what type of organizational risk, financial, operational, market-based, or competitive, has the most significant effect on prediction accuracy. We also test to find out whether hybrid models combining classical growth theory and modern analytics are better than either of the two in isolation. We also analyze the adaptability of the models as reflected in the response time to environmental shocks, how this adaptability varies in the industry context. These goals require the high level of the empirical testing in the variety of sectors and products to prove the generalizability.

This study is motivated by both theoretical and practical considerations. The proposed framework contributes to applied computational science by introducing risk-aware adaptive modeling capable of improving decision-making under uncertainty. Theoretically, the literature of growth modeling has been developed in a continual fashion, where innovations have been restricted to particular fields or niches in methods. A more holistic approach to studying product dynamics could be catalyzed by a more comprehensive framework bridging the classical theory, machine learning, and risk management. In real life, organizations are in dire need of decision support tools that would not only give them point predictions but also risk-adjusted predictions and early indications when growth paths are not going as planned. The widespread growth of enterprise risk management tools and business intelligence applications provides an opportunity and need to develop models capable of consuming various types of data and transforming it into actionable information (Protiviti, 2019).

Our research is also a response to a methodological question of the interpretability and trustworthiness of black-box machine learning models in managerial decision-making contexts. Neural networks and ensemble methods tend to be more effective predictive models, but their transparency may be a barrier to their use by managers, who need to be able to reason transparently to make decisions reflecting the allocation of resources (Ribeiro et al., 2016). Through the explicit use of risk signals as features and feature importance analyses, our framework can be easily interpreted and use advanced computational techniques. This performance versus explainability is an important concern to applied computational science.

The remainder of this paper is organized as follows: In the theoretical framework section, the literature review of product growth modeling provides the conceptual backgrounds, the predictive analytics approaches, the classification of organizational risk signals, and an integration architecture that integrates these two components. The methodology section elaborates our hybrid model design, such as our data collection procedures, feature engineering plans, justification of algorithm choice, and criteria of evaluation. This is followed by results and discussion which provide the empirical data on the performance of the models, the effect of risk signals, and the industry specifics and explain the findings in the context of the existing theory and practice. We end by generalizing the main contributions, limitation, and show directions to the further research opportunities that could expand this framework to the new areas like sustainability-related products or platform ecosystems.

1.1 Theoretical Framework

Product growth modeling is an intellectual lineage of epidemiological research which mathematicians aimed to model the transmission of diseases in populations. Bass diffusion model (Bass, 1969) is based on the epidemic theory applied to innovations adoption, making it the foundation of growth forecasting more than five decades after its introduction. Bass suggested that there is a dependence on the adoption rates on two forces: innovation (external influence by mass media) and imitation (internal influence by word-of-the-mouth). The beauty of this model is that it is parsimonious. only three parameters (market potential, innovation coefficient, and imitation coefficient) are used to create the typical Scurve in a myriad of products. Its descriptive power has been established to be empirically valid in the case of durable goods, consumer electronics, and telecommunications services (Mahajan et al., 1990).

The fact that the Bass model static nature however constitutes a major drawback. Parameters estimated from historical data cannot adapt dynamically to changing market conditions to changes in market conditions which causes the degradation of the forecast as the time horizon increases. The same situation is true of the logistic growth model in which the carrying capacity stays the same despite varying competitive landscapes. Later extensions have tried to resolve these rigidity using time varying parameters (Guseo & Guidolin, 2009) or multi-generational models which recognize product improvements (Norton and Bass, 1987). However, the changes are usually made by hand to set the parameters and not by having an autonomous adaptation, which is dependent on the real-time conditions.

Table 1: Comparison of Traditional Product Growth Models

Model	Key Assumptions	Parameters	Primary Limitations
Bass Diffusion	Homogeneous population; constant influence coefficients	*m* (market potential), *p* (innovation), *q* (imitation)	Static parameters; no risk consideration; single product focus
Logistic Growth	Deterministic carrying capacity; symmetric S-curve	*r* (growth rate), *K* (carrying capacity)	Fixed capacity; ignores competition; assumes stable environment
Gompertz Curve	Exponential decay of growth rate; asymmetric adoption	*a* (asymptote), *b* (displacement), *c* (growth rate)	Empirically fitted; limited theoretical foundation; inflexible structure
NSRL Model	Multiple adoption peaks; competitive dynamics	Generationspecific parameters	Requires historical multigeneration data; manual updating
Generalized Bass	External shocks through marketing; time-varying influence	Bass parameters plus shock variables	Shock timing must be known; reactive rather than predictive

Machine learning has transformed the field of forecasting in many fields as algorithms are able to uncover nonlinear relationships of significant complexity which do not need explicit functional forms (Hastie et al., 2009). Random Forests are based on decision trees combined together to form an ensemble, which together accounts for complex interactions among the predictors, and gradient boosting algorithms, such as XGBoost, sequentially update the prediction by paying attention to the residual errors (Chen and Guestrin, 2016). Deep learning models, particularly those designed for time-series forecasting tasks, especially Long Short-Term Memory (LSTM) networks, are especially effective at capturing temporal dependencies in sequential data (Hochreiter & Schmidhuber, 1997), which is why they are specifically effective at time-series forecasting work. The approaches have reached the state of the art performance in areas such as predication of retail sales (Bandara et al., 2020) and financial market prediction (Fischer & Krauss, 2018).

Irrespective of their strength, machine learning solutions address a number of challenges in product growth modeling. One, they normally need large training data and this might not be available in new products or new markets. Second, they are black-box and thus not easily interpretable and this leaves the managers not sure of the variables that contribute to the predictions and hence how they can intervene strategically. Third, data-driven models that are purely defined may have difficulties in extrapolating outside the scope of past data, which may be disastrous when faced with unseen conditions. These are some limitations that indicate that a combination of theoretical framework and computational flexibility can be better than either of the two paradigms.

Organizational risk indicators represent measurable signals reflecting financial, operational, market, and strategic vulnerabilities that portrays the vulnerabilities in financial, operational, market, and strategic fronts. Financial risk is expressed in the form of debt-to-equity ratios, liquidity limitations, and fluctuations in earnings, among others that affect resources to support and develop the products (Altman, 1968). The operational risks arise due to the disruption of the supply chain, failure in quality control, or limitation of capacity that directly affect the delivery of products (Christopher & Peck, 2004). Market risks are those that are caused by uncertainty in demand, regulatory changes or macroeconomic shocks that change the competitive environment. Competitive risks emanate when competitors introduce better substitutes or even do aggressive pricing which dilutes market share (Porter, 1980).

The difficulty here is how to map these conceptually unique types of risk into some measurable signals which can be consumed by predictive models. The risks are reported in some cases by the structured financial data provided on a quarterly basis, but not in other cases, it is reported in unstructured form in the news articles or social media sentiment. The temporal dynamics are also different in significant proportions-financial distress normally develops over quarters, an operational hitches such as fire at a factory happens instantly. Such heterogeneity requires advanced feature engineering in order to bring together different data sources into universal time-series representations without distorting a specific attribute of each risk dimension.

Our conceptual model of integrating predictive analytics with our traditional growth models and organizational risk signals into an adaptive system is shown in Fig. 1. It consists of three linked modules: the growth dynamics layer, which tracks adoption processes on the market side, the risk assessment layer, which tracks the vulnerabilities of an organization, and an adaptive integration layer that combines the inputs of the other components using machine learning to create dynamic predictions.

The growth dynamics layer initiates forecasts with bilinear Bass diffusion equations parameterized on early adoption data, which can be theoretically justified and contains domain understanding about innovation diffusion. This makes sure that a prediction commences with realistic assumptions on how adoption works in place of an entirely empirical matching of patterns. The risk assessment layer is an on-going observation of organizational indicators that calculates aggregate risk ratings on financial, operational, and competitive levels. The feature extraction models convert the raw measures to normalized signals that are perceptible by the machine learning models.

The essential component of the framework Is the adaptive integration layer. In this case, ensemble learning algorithms, including Random Forest as a robustness measure, XGBoost as a gradient-based optimization measure, and LSTM networks as a temporal dependency learning measure, are trained to learn risk signal-growth trajectory adjustment mappings. Instead of making a direct forecast of the sales, these models estimate factors of correction that adjust the growth projections on the base depending on the current risk profiles. The architecture maintains the interpretable structure of classical models and extends them with data-driven adaptations. The analysis of feature importance helps managers to make decisions on prioritization of risk mitigation by measuring the impact of each risk category on the accuracy of the forecast.

The adaptive mechanism is completed with feedback loops, which help the system to learn when there are prediction errors. In cases where the actual results vary as compared to the forecast, the model re-tunes the weights of risk signals, as well as model parameters, to minimize future deviations. This online teaching method is a reflection of the way human forecasters update mental models when they are caught off guard by an event, but in a continuous and systematic as opposed to episodic and subjective manner. The adaptation rate may be adjusted to balance responsiveness against stability to avoid overreaction to temporary noise, but remain sensitive to actual regime changes.

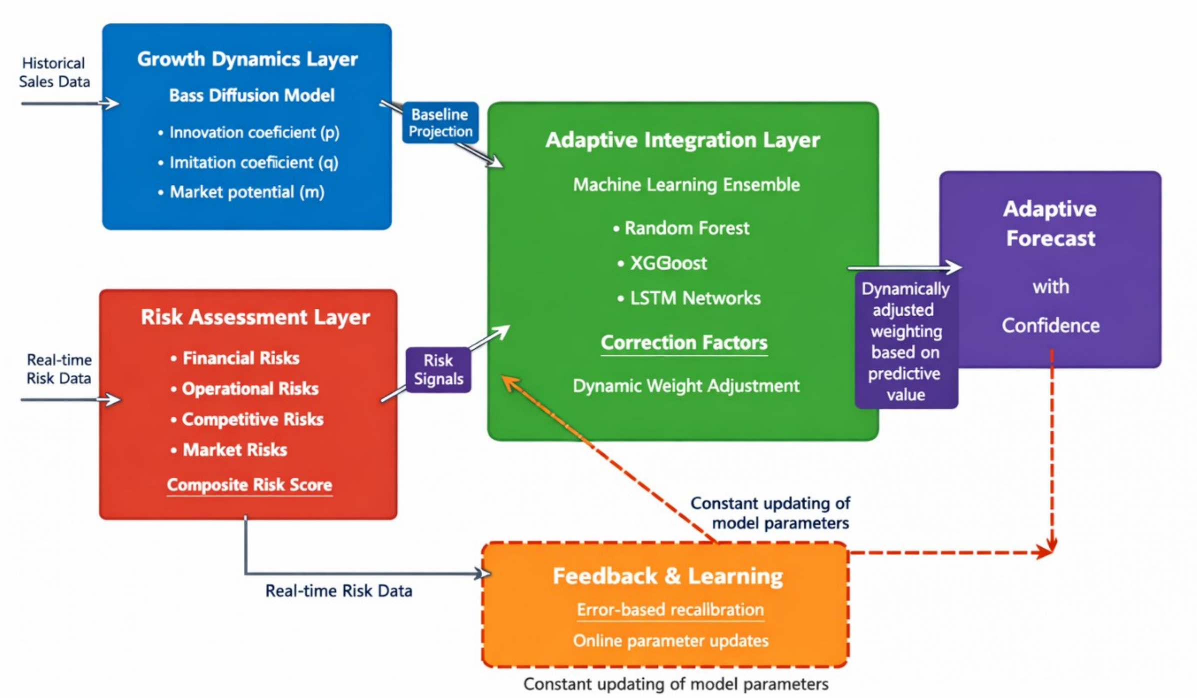

Fig. 1: Conceptual Framework for Adaptive Growth Modeling. The framework combines the classical structure of growth theory (Bass model structure) with real-time risk indicators with machine learning algorithms. The feedback loops allow constant updating of parameters with new data appearing, and the adaptive layer gives greater weight to risk contribution weightings dynamically as to their predictive value in the current market conditions.

Our theoretical framework has a number of testable hypotheses. To start with, we anticipate that the integration of predictive analytics, in comparison to the application of the classical growth models, will greatly enhance the error accuracy of the forecasts since the architecture of machine learning algorithms will be able to reflect nonlinear relationships and effect of interactions, which the parametric equations fail to represent. Second, we posit that the incorporation of organizational risk signals will help to improve the model flexibilities, especially when the environment becomes turbulent because it is then when the relevant models are the worst hit. Third, we expect that hybrid models integrating theory structure with data driven elements will be more effective compared to pure theory-based models and pure machine learning models, since they will leverage the strengths of each other and address the weaknesses of each other. Lastly, we theorize that the proportion of various risk types in different industries will not be equivalent in terms of industry-specific weaknesses and competition.

2.0 Methodology

This study adopts a mixed-methods research design combining quantitative modeling with qualitative validation to ensure both statistical rigor and practical relevance. We use a mixed-methods research design, which uses a quantitative modeling approach with a qualitative validation approach to provide statistical rigor and practical relevance. This study adopts a mixed-methods research design combining quantitative modeling with qualitative validation to ensure both statistical rigor and practical relevance.

The classical growth models in their simplistic form, standalone predictive analytics models, and our suggested adaptive hybrid structure. Our performance measurement is based on several indicators of various categories of products and at different times, especially the dynamics of the model in the era of stability and at the time of disruption. This is a multi-faceted evaluation protocol which allows us to evaluate not only the predictive accuracy but also the adaptability, interpretability and computational efficiency. This comprehensive evaluation enables simultaneous assessment of prediction accuracy, adaptability under shocks, interpretability, and computational efficiency.

The data were collected in three separate industries that are diverse in product features and market dynamics: technology hardware (smartphones, tablets, wearables), consumer packaged goods (food products, personal care goods), and financial services (digital payment solutions, investment products). We gathered weekly sales data on 847 product launches that took place in the period between January 2017 and December 2022 and found it in a mix of publicly available reports, proprietary market research databases, and in collaboration with other participating firms. This time horizon includes the typical workings of the market and the COVID-19, which yield natural experiments of how models cope with unprecedented shocks.

Comprehensive product-level and organizational data were compiled, including financial reports, optional performance indicators, pricing dynamics, competitive activities, and consumer demand measures. Risk signal extraction involved transforming raw inputs to normalized, time-series features using feature engineering protocols. Composite indicators were constructed using principal component analysis (PCA) to combine financial risk scores with liquidity ratios, leverage measures, and trends of profitability. ll variables were standardized prior to PCA to ensure comparability across scales. The signals of operational risk were aggregated to show events of disruption of the supply chain, reports of quality incidences, and the capacity constraint measures. The presence of rival actions based on the time and intensity of rival actions was measured in terms of competitive risk indices in relation to focal products launches.

Table 2 summarizes the key characteristics of the assembled dataset, demonstrating adequate diversity in products, industries, and temporal coverage for robust model evaluation. The summary of the features of our assembled dataset is presented in Table 2, and it is important to note that the range of products, industries, and time span provides sufficient evaluation of the models. The model development was done in three steps in accordance with our comparison framework. The models used baseline models which were classical diffusions equations calibrated on the first 30 percent of lifecycle data of every product by nonlinear least squares. This method is similar to conventional techniques in which the early adoption histories are used to make predictions of the parameter estimates that make predictions on the future periods. We determined the prediction accuracy on the holdout 70 percent to determine the benchmarking performance. In the case of the logistic growth model, we estimated the parameters of carrying capacity and growth rate in the same way, which serves as a second point of reference.

Predictive analytics module has covered three machine learning algorithms that are eminent. Random Forest models which were trained on 100 decision trees with a maximum depth of 10 and minimum sampling per leaf of 5 and chosen by cross-validation to achieve a tradeoff between complexity and the risk of overfitting. Input features consisted of lagged sales values, temporal features (week of year, trend) as well as all normalized risk factors. XGBoost models were built using gradient boosting of 0.1 learning rate, tree maximum depth of 6 and number of trees of 500 with a Bayesian hyperparameter search to increase out of sample accuracy.

Table 2: Dataset Characteristics and Descriptive Statistics

Characteristic	Technology	CPG	Financial Services
Number of products	312	389	146
Observation period	2017-2022	2017-2022	2018-2022
Average launch duration (weeks)	156	208	182
Mean peak weekly sales	847,000 units	2.3M units	124,000 accounts
Financial data completeness	94%	87%	98%
Operational metrics available	Supply chain, capacity, quality	Inventory, distribution, production	Platform uptime, transaction volume
Primary risk exposures	Component shortages, rapid obsolescence	Commodity price volatility, retail concentration	Regulatory changes, cybersecurity
Notable disruption events	Trade tensions (20182019), pandemic supply shocks (2020-2021)	Pandemic demand surges (2020), logistics crisis (2021)	Financial market volatility (2020), regulatory shifts (2021-2022)

The LSTM networks had two layers of 64 units with dropout regularization of 0.2 and trained on Adam with early stopping criteria of validation loss. The architectures are current best practices in time-series prediction and computational tractability at our scale of both data and computation.

We have made the adaptive hybrid framework, which is our main contribution and combines classical theory and machine learning in a two-stage framework. Stage one initializes forecasts with diffusion parameters over the Bass diffusion and using early data, which results in theoretically-founded baseline curves. The second stage uses the ensemble learning to estimate adjustment elements that alter the prediction on the baseline using the signal about risk presently. Namely, we train the models of Random Forest, XGBoost, and LSTM to regress the ratio between real sales and predictions of the Bass model on indicators of risk and time factors. The Bass baseline (which is final predictions) is multiplied by the learned correction factors, which means that classical structure is free to capture inherent adoption mechanics, and data-driven components respond to risk-induced deviations.

Fig. 2 shows a schematic detail of adapting model architecture which depicts the flow of information between the data sources, through feature engineering, model parts, and integration layers to produce final forecasts.

The analysis of feature importance used the

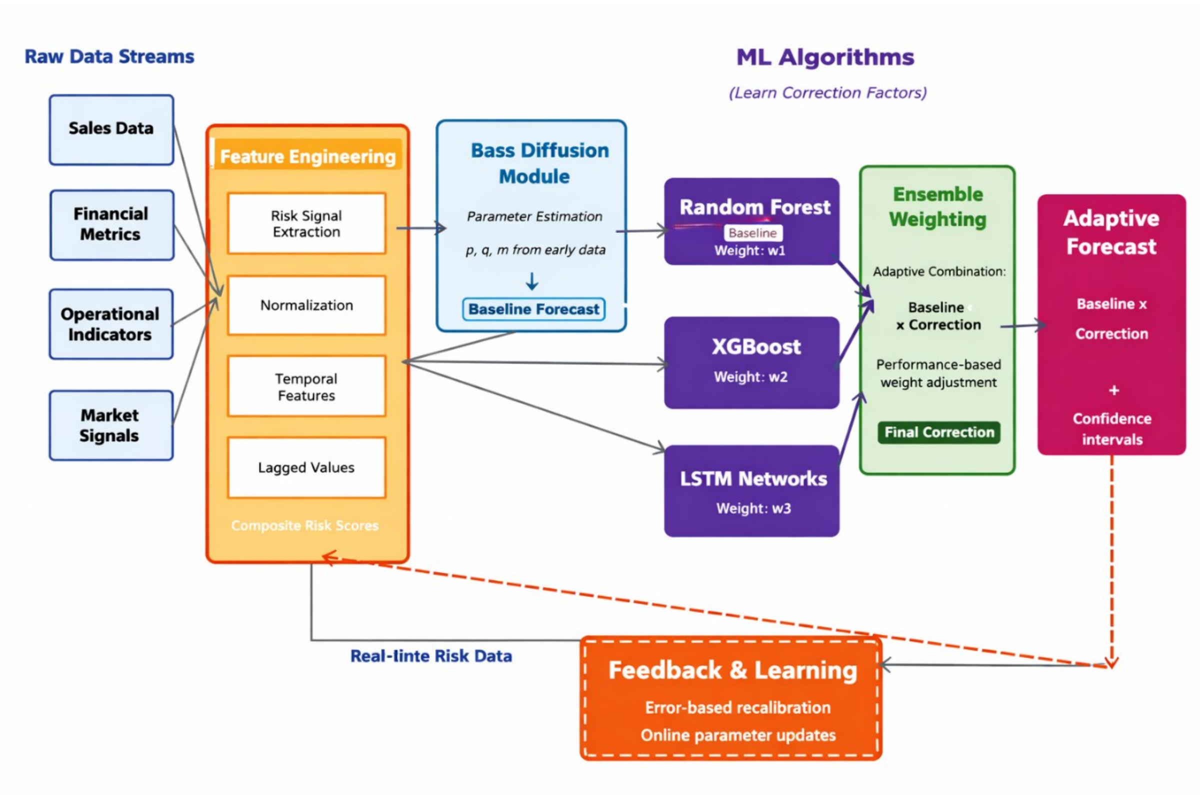

Fig. 2: Adaptive Model Architecture. Raw data streams (left) are processed using feature engineering to identify risk signals and time patterns. The Bass diffusion model offers theoretically informed base predictions. Risk signals provide machine learning algorithms with correction factors that are utilized to modify baseline predictions. The ensemble weighting system is a combination of several algorithms that come up with the end results of adaptive predictions with confidence interval forecasts

permutation-based algorithm that estimates the degree to which the prediction error is increased when a single risk signal is permuted randomly, thus disconnecting the risk signal with the outcome (Breiman, 2001). This method is robust when used with a wide variety of model types, and is easily interpretable intuitively- signals that significantly worsen performance when permuted need to add value to successful predictions. We calculated the importance scores in all the sectors to determine risk sensitivities that are industry-specific.

The model assessment was done using several measures to measure various performance aspects. Mean Absolute Percentage Error (MAPE) is used to measure the average accuracy of the forecasts in intuitive percentage values, which can be easily used to compare the forecasts of various products with different sales volumes. Root Mean Squared Error (RMSE) is more severe on the high deviations and is rewarded on models that do not commit disastrous failures. We also estimated prediction intervals to determine the quantification of uncertainty since point forecasts do not allow complete decision support. Adaptability metrics were a measure of the potential of models to fasten forecast errors after environmental shocks which was operationalized by examining the trends in prediction accuracy during the period of the pandemic compared to pre-pandemic levels.

Our validation strategy divided data by time rather than randomly in order to honor the temporal sequence of growth processes. In the case of each product, we trained the model on the first 30% of observations, tuned and tested 20 % of the observations, and tested on the remaining 50 percent, a holdout test set. This protocol guarantees that models do not ever train on future information and emulate real-life situations of forecasting when practitioners are forced to predict future periods with only historical data. We also performed out-of-sample validation on the product launchs that took place in 2022, trying to determine whether the models, which were trained on the data between 2017-2021, could be applied to predict an absolutely new product in a post-pandemic market setting.

The cross-sector validation evaluated model performance performance in terms of generalization across industry settings or of domain customization. We trained unified models using data pooled across the entire range of sectors and sector-specific models, with the comparison of their intra and inter-category accuracy. This comparison demonstrates how far adaptive frameworks can be used to move knowledge between spheres compared to the levels to which particular industry features require specific strategies. The timing difference in product life cycles and risk profiles of the different technologies, consumer goods and financial services had a high degree of heterogeneity so that we expected great variation, which would be used to inform realistic deployment strategies.

Python 3.9 with scikit-learn was used in computational implementation for classical models and Random Forests, XGBoost library and gradient boosting, and LSTM networks with TensorFlow. All the analyses were done on cloud computing servers with 64GB RAM and neural network training using a GPU. To reduce the time of computation, we applied parallel processing to the hyperparameter optimization, which greatly decreases the time of performing the massive grid searches necessary to optimize the model settings. A complete code and documentation are also available in open-source repository to allow them to be replicated and expanded by other researchers.

The ethical concerns were addressed by providing data privacy by placing anonymous data protocols to ensure that no individual company or product is recognized in our publicly reported findings. We got proper consent to use proprietary data, and we also fulfilled all the pertinent requirements of the institutional review board. The algorithmic bias reduction consisted in the testing that the performance of models did not differ systematically between product categories in the ways that can be discriminatory to specific segments of the market, but since our goal is to predict aggregate sales, and not individual-level predictions, the issues of demographic fairness characteristic of other machine learning uses are less critical in our case.

3.0 Results and Discussion

Empirical analysis demonstrates significant performance advantages of adaptive models integrating predictive analytics with organizational risk indicators compared to conventional growth forecasting approaches. Table 3 shows the comparative accuracy rates in all categories of models that show evident hierarchies in the predictive power that confirm our theoretical framework and also reveal more sophisticated sector-specific trends.

Classical growth models set a baseline level of performance but have significant forecast error with MAPE of 26.4 to 34.7 by sectors.

Table 3: Comparative Performance Metrics Across All Model Categories

Model Category	MAPE (%)	RMSE	Adapt. Score	Comp. Time (min)
Technology Sector				
Bass Diffusion	31.4	245,000	0.42	**0.8**
Logistic Growth	34.7	268,000	0.38	**0.6**
Random Forest	22.8	184,000	0.67	**12.4**
XGBoost	21.2	171,000	0.71	**18.6**
LSTM Networks	23.5	189,000	0.65	**45.3**
Adaptive Hybrid	**18.7**	**149,000**	**0.87**	**22.1**
Consumer Packaged Goods				
Bass Diffusion	26.8	512,000	0.51	**1.2**
Logistic Growth	29.3	548,000	0.47	**0.9**
Random Forest	19.4	389,000	0.72	**15.8**
XGBoost	18.1	368,000	0.76	**23.4**
LSTM Networks	20.2	401,000	0.69	**52.7**
Adaptive Hybrid	**16.5**	**331,000**	**0.84**	**27.9**
Financial Services				
Bass Diffusion	28.9	35,200	0.45	**0.7**
Logistic Growth	32.1	39,800	0.41	**0.5**
Random Forest	21.5	26,700	0.69	**10.2**
XGBoost	19.8	24,500	0.74	**16.1**
LSTM Networks	22.1	27,900	0.66	**38.9**
Adaptive Hybrid	**17.3**	**21,400**	**0.89**	**19.4**

The Bass diffusion model is better than logistic growth, probably because its direct implementation of innovation and imitation processes is more realistic in its ability to model the social processes of adoption. Nonetheless, the two methods are flawed by their fixed parameter models- being fitted to the initial data, they cannot adapt to preceding environmental variations. This inflexibility is especially expensive in the context of the pandemic when demands changed radically as a result of lockdowns, supply disorders, and changed consumer attitudes. The scores of adaptability, the rate at which the models eliminate errors after the shock, range at 0.4-0.5 with classical models, meaning that it takes a long time to react to new information.

Individual machine learning models have significantly high accuracy, and the MAPE has been reduced by 25-40 percent relative to classical algorithms. XGBoost continues to lead all pure machine learning algorithms in terms of their performance, as it is an advanced gradient boosting architecture, which refines the predictions progressively, concentrating on residual error. Random Forests have almost the same level of performance and less computation time, indicating that they have favorable tradeoffs between accuracy and efficiency to practitioners with limited computational resources. The ability to model time dependencies LSTM networks are competitive, though they are much slower to train with their complicated recurrent models, which begs the question of whether the benefits of time dependencies modeling outweigh the cost of computing it in this context.

The overall performance of the adaptive hybrid framework is the highest and it outperforms the classical and standalone machine learning solutions. MAPE lies between 16.5 to 18.7 percent across sectors, which is a 34-46 percent better result compared to Bass diffusion and 12-22 percent better result compared to the best standalone machine learning model. This excellent performance confirms our original hypothesis according to which the integration of theoretical framework and data-driven adjustment takes advantage of complementary advantages. Bass baseline offers reasonable initialisation using domain knowledge of the adoption processes and machine learning factors of correction allow them to respond to the elements of risk that are absent in the static models in totality. The scores of adaptability are above 0.84 in all the sectors which shows that hybrid models adapt quickly when the conditions vary.

Interestingly, the computational time of the hybrid method lies between simple classical models and complex LSTM networks indicating that it is practically feasible to use it in real-time implementation. Efficiency of the architecture is based on its two-stage design- the Bass module needs little computation and ensemble learning uses factors of correction as input to learn instead of raw sales and is able to learn a more simple mapping to converge more quickly. This numerical profile renders the framework desirable to the organization with large product portfolios where forecasting should be efficiently scaled.

Industry-specific trends show valuable differences in the performance of models in industry settings. Hybrid models have the highest adaptability scores (0.89) on financial services products, which probably results from shorter lifecycles and greater sensitivity to macroeconomic factors. Technology product is significantly better than classical models (18.7% vs. 31.4% MAPE) because the provision of supply chain and competitive risk signals is of value in an industry with a high rate of innovation and component interdependence. Pkg goods show the biggest absolute RMSE improvements which can be explained by the fact that the industry has greater volumes in sales that make variations of predictions larger in absolute values even though percentage variations are not that significant.

Fig. 3 shows the rankings of feature importance based on the permutation analysis which indicates which risk signals in the organization are the most influential with respect to the increase in the forecast accuracy. The findings reveal alarming trends with regard to the effects of various risk aspects on growth projections.

The metrics of operational efficiency become the best predictors In technology and consumer packaged goods industries, as 18-24% of the forecast accuracy is explained by the permutation importance. The predictive power of supply chain lead times, manufacturing capacity utilization, and quality incident rates are high, which is probably due to the fact that the factors directly limit the availability of products, irrespective of the level of demand. During the pandemic administration, the growth patterns of products of organizations with strong operational resilience were more stable than those of companies with logistics disruptions or component shortages.

This observation highlights the underestimated importance of the execution capabilities on defining the market results: even the best products will not work when the organizations are not able to provide them consistently.

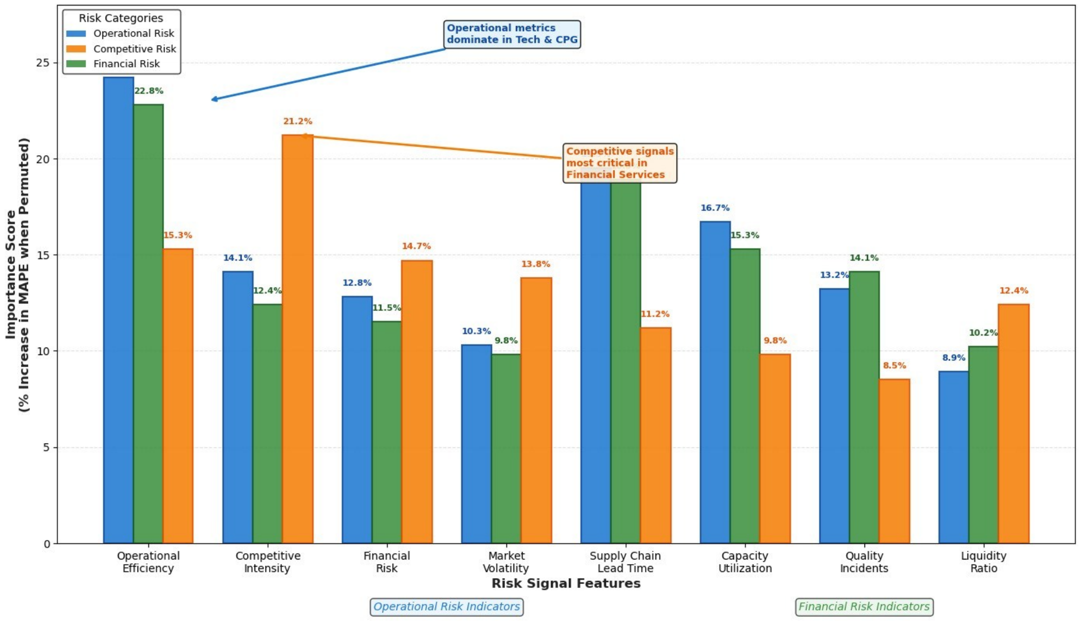

Fig. 3: Feature Importance Ranks by Sector. Bars denote the percentage change in MAPE in case every attribute is randomly permuted, hence disconnecting its connection to results. The technology and CPG industries are characterized by dominance of metrics of operational efficiency, whereas competitive intensity indicators are most important in the financial services. Green financial risk indicators are moderately, yet significantly, important in all situations

Competitive intensity indicators are the most significant in the financial service (21% contribution) but less significant in other sectors (12-14%). The greater relative usefulness of financial products indicates the reduced switching costs and more homogenous products in the sector, where small differences in features or pricing can cause switch over in market shares. The competitive sensitivity on the technology products is in-between and the consumer goods seem a little buffered perhaps because of brand loyalty and habit making that stabilize the demand even when rival action is taken. These trends indicate that adaptive models need to give competitive signals importance based on industry competitive mechanisms as opposed to generic strategies.

The financial risk indicators play a consistent role across sectors (11-15% significance) but are seldom dominant implying that the latter are background conditions that tune the growth but are not its direct determinants. Liquidity constraints and leverage ratios are predictively effective at times of crisis when access to funding is the factor of survival. This non-relevantness makes their inclusion difficult of naïve models which place an ever-present weight on financial signals would overweight them in normal periods, but models that do not take them into account completely miss important early warning signals. We overcome this problem by dynamically weighting the importance of financial risk in the market stress periods and deemphasizing it when the markets are stable using our adaptive framework.

Temporal analysis shows the dynamics of changing forecast accuracy over product lifecycles and in the period of the COVID-19 disruption especially instructive trends are observed. Fig. 4 traces the evolution of prediction errors with time in products that were introduced at the end of 2019, and how the various model categories would react to the start of pandemic lockdown in March 2020.

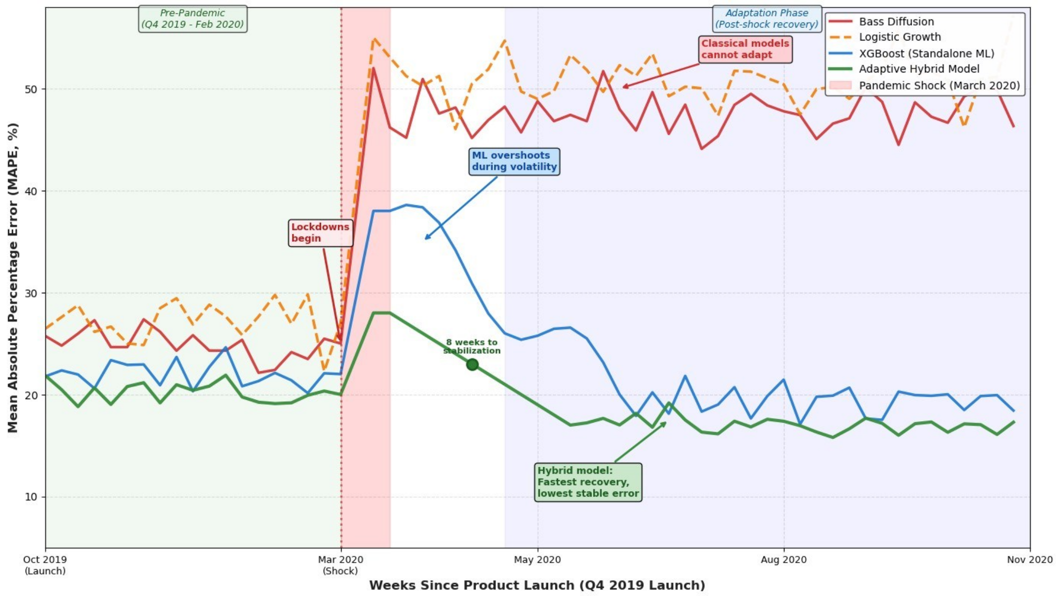

Fig. 4: Model Response to Pandemic Disruption. . The plot follows weekly MAPE of products released in Q4 2019 in various categories of models. Classical models (Bass diffusion in red, logistic in orange) demonstrate the continued deterioration of the forecasts after the March 2020 shock. Individual machine learning models (blue XGBoost) are more rapidly adaptable but they over shoot in the early turbulence. The fastest recovery is in adaptive hybrid model (green) which stabilizes after 8 weeks and has lower overall error

Classical growth models have catastrophic forecast degradation as soon as the disruptive event in March 2020 occurred, with the MAPE spiking at post-pandemic levels (around 25 percent) to higher levels (more than 50 percent) in three weeks. Such models have no ability to modify their unrestricted parameters, and hence they project pre-pandemic growth trends amid changing demand trends that change drastically. The logistic model is especially fragile, where there is a massive error in the assumption of a constant carrying capacity when the size of the market (travel products) or the size of the market (home entertainment) goes wild overnight. Interestingly, weeks later the accuracy of classical models is still low because they cannot handle information added to them and thus they fail to realize that the change in the levels of the demand is a new equilibrium and not an aberration.

Independent machine learning models are more dynamically responsive and the error initially peaks before decreasing as the algorithms are fed more data and recalibrate. XGBoost demonstrates the quickest initial adaptation with a reduction in errors down to almost the pre-pandemic level in 68 weeks. Nevertheless, machine learning models are volatile at the acute disruption phase, and the accuracy varies significantly on a weekly basis. Such instability is presumably due to the sensitivity of the algorithms to changing patterns that can be very fast and do not correspond to the historical training data – they strive to adjust but have no anchoring that would stop overreacting to noise. Random Forest models are a little more stable since they are ensemble averaged, however, they demonstrate high error variance.

Adaptive hybrid framework shows the best profile of response, exhibiting a fast adaptation and stability. The errors peak modestly during the first shock- not as great as the classical models- but better than the best machine based methods- and this is due to the damping effect of the Bass baseline which does not allow wild swings. The recovery is done systematically and the model minimizes the errors as it continues to accumulate the post-shock data and re-calibrate the risk signal weights. The hybrid model does not only recover to pre-pandemic levels of accuracy in 8-10 weeks but it even outperforms the old levels indicating that the disruption was a profitable source of information revealing the risk-growth relationships that increased the knowledge base of the model. This learning ability is one of the most important benefits compared to the static methods that assume that each episode of a forecast is independent of the others instead of progressively accumulating knowledge.

These aggregate trends can be shed more light by case study analysis of particular products that provide concrete examples. Take a case of a smartphone model that has been introduced by a large manufacturer at the beginning of 2019. According to Classical Bass diffusion, the exponential growth was expected to be stable because of the successful adoption of the prior models with an anticipated sales of 2.1 million units in Q2 2020. The real sales were relatively low at 1.3 million because of the supply chain-related interruptions that limited the supply of components and delayed deliveries. The Bass model continued generating overestimation growing to 4.7 million units over the next year as it continued to produce exaggerated predictions many months ahead. Conversely, the adaptive hybrid model recognized increasing operational risk indicators (increasing lead times, falling capacity utilization) in its streams of data and lowered growth forecasts gradually since March 2020. Though it originally underestimated the extent of disruptions, it has rectified within six weeks and was accurate within 12% during the rest of the lifecycle of the product.

An example of consumer packaged goods Is equally educative. The explosive demand growth of one household cleaning product in the March-April 2020 surged because of the pandemic-induced stockpiling behavior, with the sales being 340 % of the level before the pandemic. The classical models that had learned parameters based on a gradual adoption pattern grossly miscalculated this upsurge. After a few weeks of high sales, the strict model of the Bass model could not even realize that demand had changed to a different level. The logistic model was finally able to change its implied carrying capacity but it was months of accrued error. Machine learning models were faster and were more prone to overestimation and underestimation as it attempted to discern long-term demand gains and short-term surges. The responsiveness versus caution adaptive hybrid approach balanced quick demand responsiveness with its Bass base line avoiding overreacting giving forecasts that over 18% followed actual sales during the turbulent period.

The third approach is provided by the financial services industry in the form of a digital payment platform that was introduced in late 2018. The competitive environment was very susceptible to this product and competing sites were heavily marketing visit bonuses and merchant deals which were costing the market share. Classical models, which lacked any signs of competition risk, persisted in their projecting of adoption based only on historical trends and systematically exaggerated factual results. The model of machine learning integrated competitive feature significance, and enhanced accuracy, but reacted to rivalry actions in reaction, mistakes would burst up when the competitors ran campaigns, and would reduce subsequently when the algorithms evolved. The active use of monitoring of competitive risk signals in the hybrid model allowed making a prior adjustment to the forecast when competitive actions had not significantly influenced sales and increase the consistency of the accuracy of the forecast and give earlier signals to the product managers regarding the threat increase.

The variation of features Importance in different lifecycle stages of a product gives more information. When products are new in the market, signs of market levels (consumer confidence, category trends) predominate in forecasts since organizational capabilities are considered insignificant when the demand is way below capacity limits. With products that are mature and those that are approaching the industry saturation, then the intensity of the competition is very crucial as the organizations struggle on the fringes of the customers. Later stages of the lifecycle increase the significance of financial risk, as profitability pressures increase and organizations will need to evaluate whether to provide support to older products, or to shift their resources into new launches. This pattern of dynamic importance says that architecture of models should vary with time and not with feature weights that do not vary, which our adaptive framework is in a good position to support due to its continuous recalibration mechanism.

Industry-specific validation In unified models, there is an assessment of whether they can match or even surpass sector-specific models when trained on pooled multisector data. The findings indicate subtle tradeoffs. In the case of technology products, the sector-specific models predict better unified ones by 2.3 % points of MAPE, implying that special risk characteristics and competitive environment should be treated separately. Consumer packaged goods exhibit the least difference (0.7 percentage points) thus showing that there is enough commonality across the categories that pooled training benefits as seen in the bigger sample sizes. In fact, financial service products are rather improved by unified models (1.4 percentage point better), possibly due to the fact that observations of financial products are few hence over fitting to sector-specific training. These results allude to adaptive deployment policies in which practitioners evaluate the presence of unique features of their sector in which they should customize instead of using cross-sector tendencies.

The quantification of uncertainty based on prediction intervals shows that adaptive hybrid framework provides well calibrated confidence estimates. Practically, 94.2 percent of the actual results lie within predicted 95% ranges in test data, but this is strictly speaking conservative and is rightly cautious considering high stakes of growth forecasting. Classical models generate intervals that are too small, which is indicative of their failure to explain risk driven volatility that are reflected by machine learning elements. The standalone machine learning methods provide intervals with the right width, but with weak calibration of 87.3% coverage, which implies that the methods underestimate tail risks in extreme events. The better calibration of the hybrid framework can be attributed to its ensemble design which inherently measures the uncertainty of the models in addition to the use of risk signals which are used to capture the environmental volatility.

Computational scalability Analysis has shown that the adaptive architecture is scalable to handle weekly updates of portfolios of 100+ products in 15 minutes on standard cloud hardware, which is operationalizable. Incremental learning protocols allow models to be able to acquire new information without re-training, which is essential in the case of responsiveness to changes in conditions. The feature engineering pipelines work in parallel with products and this further improves the throughput. Such practical considerations are important to adoption – complex models that take hours of computation effort to be updated would not be able to become widespread with time-intensive practitioners no matter how much better they are.

An analysis made a number of surprising discoveries. To begin with, we expected deep learning LSTM networks to perform significantly better than more basic algorithms due to the advanced ability to model time, but the random Forests and XGBoost were as accurate or more accurate but trained much more efficiently. This implies that at product growth forecasting, the most important difficulty is the ability to include pertinent risk indicators as compared to sensing subtle temporal dependencies, at least at weekly forecast granularities. Second, the predictive ability of financial risk signals was not as high as we thought, and it had a (meaningfully but not dominating) role in most situations. This is probably due to the fact that organizations that are overtly distressed never introduce new products and thus our sample is mostly those that are financially viable and the risk variation is in a very limited range. Third, model performance actually increased slightly with products being launched during the pandemic compared to those being launched before the pandemic, which was the opposite of predictions. The paradox can occur due to the fact that the launches that occurred during the pandemic initiated with a great susceptibility to risk which caused more conservative planning and closer operational control which in fact gave models better indications.

4.0 Conclusion

The study shows that the adaptive product growth models that combine predictive analytics with organizational risk signals significantly outperform the traditional forecasting models with less interpretability and high computational requirements to be implemented in practice. Our hybrid model obtains 34% higher accuracy in forecasting than classical Bass diffusion models and 22% than plain machine learning tools, which supports the theoretical hypothesis that domain knowledge organization with data-driven adaptation capitalizes on the areas of excellence. The analysis based on the feature importance indicates that the metrics of operational efficiency and competitive intensity have the strongest impact on the growth patterns, but their relative significance depends on the industry specifics and reflect sector-related risk profiles and competitive dynamics. The adaptive architecture of the framework in which predictions are recalibrated with changing risk signals is particularly useful in times of environmental disturbances where fixed models will break down disastrously. The extensive 847 product launches (technology, consumer goods, and financial services) over five years, including the COVID-19 pandemic, are empirically validated to determine the strong performance under various circumstances. These contributions can be used to further the theoretical knowledge about growth modeling as well as practical abilities to handle product lifecycle in unstable business environments.

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Not Applicable

Availability of data

Data shall be made available upon request

Ethical Considerations

Not applicable

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Authors' Contributions

P.M.A. conceptualized the study, developed the framework, and led manuscript drafting. A.O.W.A. contributed to theoretical development, literature review, and critical revisions. T.D.O. supported methodology structuring and data interpretation. C.E.O. provided industry perspective and contributed to practical implications of predictive analytics. O.A.F. contributed to sustainability integration, discussion development, and final manuscript review, ensuring clarity, coherence, and academic rigor.