A Business Intelligence Framework for Short-Term Consumer Demand Forecasting Using Public Macroeconomic Indicators

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Abstract

Business intelligence has emerged to be a high-level managerial competency among organizations that aim to enhance the quality of planning, responsiveness in operations and evidence-based decision making in uncertain market environments. Short-term demand forecasting is one of its most important business applications since fluctuations in demand expectations affect budgeting, inventory planning, staffing, procurement timing and revenue management. The paper formulates and tests a business intelligence system of consumer demand prediction over short-term with the help of the public macroeconomic variables. It aims to show how external economic signals may be converted into an explainable, reproducible, and useful forecasting layer to be used in dashboards and decision support systems. The research forecasts next-period real consumer spending using lagged indicators based on output, disposable income, investment, unemployment, inflation, and short-term interest rates using a publicly available U.S. macroeconomic data, which is periodically updated. Ordinary least squares, ridge regression, random forest and gradient boosting are compared by using a chronological holdout design. The empirical findings indicate that the regression-based models that are interpretable have the best out-of-sample performance, and ordinary least squares model has the lowest error and greatest explanatory power. The results suggest that effective business forecasting support can be offered using transparent analytics without the need to use complex black-box models. The study is valuable because it adds to the body of business intelligence literature a reproducible external-signal prediction pipeline, a comparison of the explainable and non-explainable models in a management context, and a translation of the forecasting results into operational and strategic planning consequences.

Keywords: Business intelligence; business analytics; Demand forecasting; Decision support; Predictive analytics; Consumer demand

1. Introduction

Companies are currently working in a more uncertain business environment that is more shock-prone in purchasing power, and more prone to shifts in financing terms as well as increasing the demands to support managerial choices by credible evidence. Under these circumstances, business intelligence (BI) has developed into a reporting role into a wider management tool incorporating data acquisition, transformation, analysis, visualization, and decision support. The previous BI work was focused on data warehousing, reporting, and descriptive dashboards, but the area has grown to encompass predictive and prescriptive applications to aid planning, prioritization, and business control [2, 5]. This development applies especially to companies that must be able to forecast the changes in the market demand in the short term, and adjust operational choices before the impact of those changes may become entirely evident.

One of the most useful business applications of BI is short-term demand forecasting due to the influence it has on a range of management processes that are interconnected. Consistent predictions affect revenue objectives, budgetary assumptions, purchasing schedules, replenishment choices, human resource planning, and marketing timelines. Inaccurate demand predictions in retail and service settings can cause direct and indirect losses due to stockouts, unnecessary inventory, underutilized capacity, ineffective campaign timing, and unnecessary working-capital pressure [7, 18]. Consequently, demand forecasting could not be perceived merely as a statistical endeavor. It must be part of a wider BI platform where information is converted to managerial indicators that could be used to take action.

Recent research has also revealed that organizations are integrating BI with business analytics and predictive analytics to enhance responsiveness of managers and responsiveness to strategies. Research in the banking sector, tourism, and supply chain management, as well as in public-sector organizations and SMEs, has shown

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that the adoption of BI can lead to better quality in decisions, better visibility of the state of operations and to reinforce organizational performance provided that it is backed by an analytical culture and appropriate capabilities [6, 9, 15, 16, 19]. Meanwhile, not every organization has proprietary, large-scale data assets or established analytics infrastructures. It is because of this reason that managers frequently require forecasting methods that are clear, inexpensive, understandable and founded on dependable external sources of data as opposed to very bespoke internal systems.

Such a forecasting layer can be based on public macroeconomic indicators. Disposable income, investment, unemployment, inflation, and short-term interest rate are some of these variables, which capture the overall economic condition that determines consumer spending and hence the aggregate demand conditions. These variables can serve as external intelligence signals in a business point of view. They assist the managers not just to understand what demand is likely to be in the next period but also why the demand is likely to be changed. This ability is aligned to the logic of BI: to convert the data available into contextualized business knowledge that can be acted upon.

In spite of this potential, there are two gaps that are apparent in the literature. First, a lot of research in business forecasting focuses on the development of technical models but pays less attention to managerial interpretation and BI integration. Second, there are numerous BI papers that are conceptual, adoption-oriented, or industry-specific that do not demonstrates a reproducible empirical pipeline on publicly available data. Moreover, the practical question of whether explainable regression-based models can be competitive compared to more flexible machine-learning strategies in business forecasting environments is so far unanswered by the recent research, although it is open to discussion [1, 13, 14].

In line with this, the present paper builds a BI model of short-term consumer demand prediction based on the U.S. macroeconomic measures of the public. The paper forecasts next-quarter real consumer spending using lagged economic variables and contrasts the forecasting of ordinary least squares, ridge regression, random forest, and gradient boosting. Three times the contribution is made. To begin with, the paper provides a low cost and fully reproducible forecasting workflow using public data [8, 17]. Second, it compares business worth of explainable models to the more complex black-box models in a managerial forecasting context. Third, it views the empirical outputs as decision-support messages pertinent to planning, budgeting and operational preparedness instead of defining prediction as a distinct technical exercise.

The rest of the paper follows the following structure. Section 2 considers the recent literature and places the study in context with recent BI and forecasting studies. Section 3 gives the research model and hypotheses. Section 4 describes the data and methodology. Section 5 presents the empirical results. The theoretical and managerial contributions are discussed in Section 6. Section 7 is a conclusion to the paper.

2. Literature Review

2.1. Business intelligence as a decision-support capability

BI has moved beyond its earlier identity as a reporting environment and now functions as a broader managerial capability that connects data infrastructure with strategic and operational decision-making. Recent literature has emphasized that BI and business analytics create value when they strengthen decision routines, cultivate analytical culture, and improve the organizational ability to detect signals and respond coherently [6, 13, 19]. In banking, BI adoption improves decision-making performance when technological and organizational conditions align [15]. In public-sector settings, data-driven culture, data literacy, and knowledge management have been linked to stronger analytics capability and decision performance [6]. These studies collectively indicate that BI contributes not only by processing data but also by structuring how organizations reason, coordinate, and prioritize action.

A second stream of recent research focuses on BI and related analytical systems across sectors. In tourism, BI and BA were found to play distinct yet complementary roles, with BI contributing more strongly to operational integration and BA contributing more strongly to predictive customer-facing applications [9]. In financial decision contexts, automated BI systems have been linked to stronger data processing, more timely performance analysis, and improved managerial actionability [21]. In SMEs, management accounting has also been framed as a BI system that affects both financial and non-financial performance through better intelligence activities and strategy alignment [16]. Across contexts, the recurring message is that BI is most valuable when it is connected to a concrete managerial task and translated into actionable business signals.

2.2. Demand forecasting as a business intelligence application

Demand forecasting remains one of the most visible business use cases for analytics because it directly influences revenue, inventory, and capacity decisions. Recent literature argues that retail forecasting should be viewed as a support system embedded in business processes rather than a narrow modeling exercise, while also emphasizing that forecasting environments differ significantly by product context, lifecycle, and operational complexity [7, 18]. Research in automotive spare parts, retail, and planning-oriented supply chains continues

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to show that forecasting quality affects working capital, service levels, and operational stability [4, 14, 20].

Recent forecasting studies also illustrate a tension between methodological sophistication and practical interpretability. Deep learning and hybrid approaches can deliver improvements in some settings, especially where the data exhibit strong nonlinearities, many cross-sectional series, or rich exogenous information [14]. However, studies on judgmental forecasting adjustments, collaborative planning, and demand planning tools suggest that managers still need interpretable signals that can be discussed and challenged during planning cycles [3, 4]. Forecast quality therefore matters, but so does forecast explainability. This is consistent with the BI perspective: a model should support managerial understanding, not merely produce a numerical estimate.

2.3. Predictive analytics, explainability, and managerial adoption

A third stream of literature concerns the relationship between predictive analytics and organizational decision quality. Several recent papers indicate that predictive analytics becomes most valuable when embedded within organizational readiness, digital transformation, and decision-support practices rather than deployed as a stand-alone technical artifact [1, 12, 13]. In Oman, for example, predictive analytics mediated the relationship between digital technology adoption and supply chain excellence [1]. Related work also suggests that integrating AI and BI can strengthen decision-making while raising practical concerns related to governance, explainability, and managerial trust [13].

Recent meta-level and bibliometric work has further shown that BI research is expanding into new domains but still leaves underexplored links between BI, decision processes, and organizational behavior [11]. Studies on analytical culture and centralization also remind us that analytics do not automatically create decentralized or superior decisions; instead, they reshape authority, information asymmetry, and how organizational actors interact with evidence [19]. As a result, a business paper in this domain should not simply ask whether a model predicts well. It should also ask whether the model can be meaningfully embedded into real business decisions.

2.4. Research gap and study positioning

The recent literature provides rich insights into BI adoption, demand forecasting methods, and analytics-driven decision-making; however, there is still a limited number of studies that combine the following features in one design: (1) a fully reproducible public dataset, (2) a clear BI framing rather than a purely technical forecasting framing, (3) explicit comparison between explainable and more complex models, and (4) translation of forecasting outputs into managerial implications for planning and control. Existing forecasting studies often prioritize model design over BI integration, while several BI studies emphasize adoption, capability building, or sectoral conceptualization rather than reproducible predictive workflows.

This study addresses that gap by developing a forecasting layer that can be interpreted as a BI artifact. It uses public macroeconomic indicators, predicts next-quarter consumer demand, compares interpretable and more complex models, and discusses the findings in terms of budget planning, operating readiness, and managerial signal interpretation. This positioning makes the paper suitable for a business journal because the core contribution lies in decision-support design and managerial interpretation rather than algorithmic novelty.

2.5. Comparative summary of recent studies

Table 1 summarizes recent studies most relevant to the present work and highlights the remaining gap addressed by this paper.

Table 1: Summary and comparison of recent studies related to BI, predictive analytics, and demand forecasting

Year	Study	Context / method	Main contribution	Gap relative to this paper
2022	[14]	Retail demand forecasting; deep learning and hybrid DSS	Demonstrates the value of advanced predictive analytics for short-, medium-, and long-term retail demand forecasting.	Strong technical emphasis; less focus on BI framing, explainability, and public-data reproducibility.
2022	[7]	Retail forecasting review	Repositions forecasting as an embedded support system affecting supply-chain and profitability outcomes.	Review-oriented; does not provide a reproducible public-data BI experiment.

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Year	Study	Context / method	Main contribution	Gap relative to this paper
2024	[19]	Survey of firms; managerial science	Shows the importance of analytical culture, top management support, and data quality for data-driven decision-making.	Focuses on organizational mechanisms rather than forecasting design and empirical demand prediction.
2024	[15]	Jordanian banking sector; PLS-SEM	Finds that BI adoption positively improves decision-making performance.	Adoption-oriented; does not compare forecasting models or public datasets.
2024	[9]	Tourism; bibliometric plus qualitative review	Distinguishes BI and BA roles in operational integration versus predictive customer engagement.	Sectoral and conceptual; no forecast experiment or model comparison.
2024	[11]	Bibliometric analysis	Identifies research trends and underexplored links between BI and decision processes.	Meta-level overview; no empirical BI forecasting workflow.
2024	[3]	Social media signals for new-product demand adjustment	Shows that social-media and sentiment signals can support judgmental demand forecast adjustments.	Context-specific and not centered on public macroeconomic BI signals.
2024	[18]	Systematic review of fashion forecasting	Synthesizes forecasting challenges in short life-cycle products and highlights method-context fit.	Review paper; not a general BI forecasting pipeline with managerial interpretation.
2024	[10]	Supply chain review	Reviews the role of DL/ML in supply-chain tasks including demand and sales estimation.	Review article; limited emphasis on explainable business-facing forecasting.
2025	[1]	Oman manufacturing/logistics; PLS-SEM	Shows that predictive analytics mediates the effect of AI/BI/DT on supply-chain excellence.	Demonstrates analytics value but does not operationalize a reproducible forecasting model.
2025	[6]	Indonesia public sector; SEM	Connects analytics capability, data literacy, and knowledge management with decision performance.	Organizational-capability focus; does not address demand forecasting.
2025	[13]	AI-enhanced BI conceptual/empirical study	Highlights synergies and challenges in combining AI and BI for decision-making.	Does not test whether explainable models can outperform more complex ML on a business forecasting task.
2025	[21]	Automated BI in financial decision-making	Shows that automated BI can strengthen financial analysis and managerial response.	Focuses on finance analytics implementation rather than macro-signal demand forecasting.
2025	[4]	Joint forecasting and analytical tool case study	Demonstrates the importance of collaboration and analytical tooling in demand planning.	Case-specific; lacks a transparent public-data benchmark comparing model families.
2025	[16]	Portuguese SMEs; SEM	Frames management accounting as a BI system linked to performance and strategy.	Performance linkage is valuable, but there is no predictive demand model with out-of-sample testing.
2025	[12]	Managerial decision support and BI education	Emphasizes the need for practical BI competence in supporting managerial decision-making.	Educational focus; no empirical forecasting exercise.
2025	[20]	Automotive spare parts forecasting comparison	Compares statistical and ML methods for demand forecasting in a sectoral context.	Operationally relevant but not framed as a BI architecture with explainable external signals.

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3. Research Model and Hypotheses

The conceptual logic of the study is shown in Figure 1. The framework treats public macroeconomic indicators as external business intelligence signals. These signals are first transformed through lagged feature engineering so that the forecasting exercise respects managerial information availability at the decision point. A forecasting engine then converts the transformed indicators into a next-quarter demand estimate, which can be surfaced in a dashboard environment and interpreted for budgeting, inventory planning, procurement timing, and operating readiness.

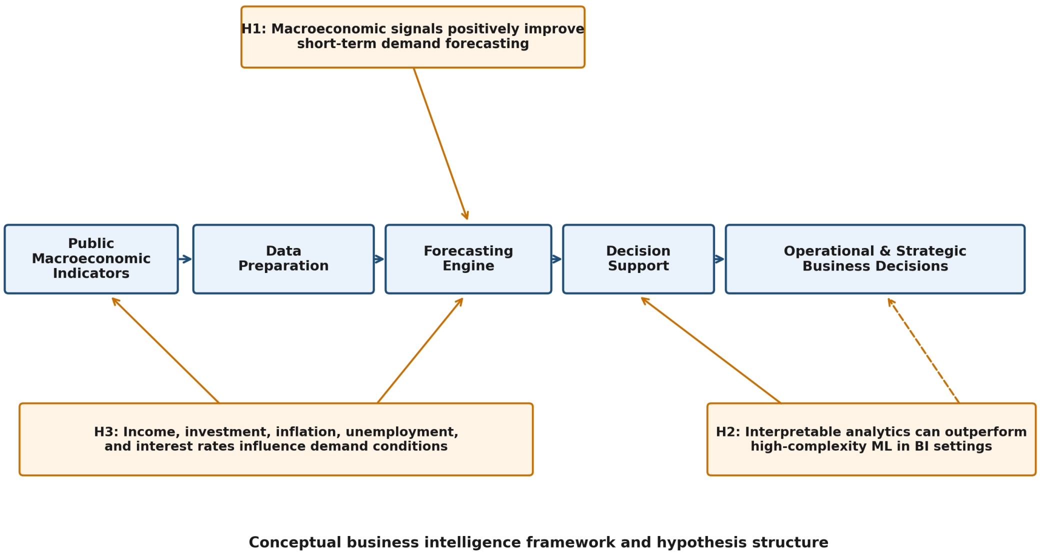

Figure 1: Conceptual business intelligence framework and hypothesis structure

The first hypothesis concerns the business value of public macroeconomic indicators. If these indicators capture changes in purchasing capacity, price pressure, labor-market conditions, and financing conditions, then they should provide useful information for forecasting near-term demand.

H1. Lagged macroeconomic indicators significantly improve the prediction of next-quarter consumer demand.

The second hypothesis addresses the tension between model complexity and practical explainability. Recent forecasting work often emphasizes flexible machine-learning approaches, yet managerial settings frequently require transparent relationships that can be interpreted and discussed during planning. This motivates a direct comparison between explainable regression-based models and more complex machine-learning models.

H2. Interpretable regression-based forecasting models can achieve performance comparable to or better than more complex machine-learning models in this BI forecasting setting.

The third hypothesis concerns the directional role of the main macroeconomic drivers. Disposable income and investment are expected to support consumer demand, while inflation and tighter short-term rates are expected to weaken it. Unemployment is also expected to shape demand conditions through labor-market effects.

H3. Income, investment, inflation, unemployment, and short-term interest-rate conditions have significant predictive relationships with next-quarter consumer demand.

4. Data and Methodology

4.1. Dataset and variables

The empirical analysis uses the public U.S. macroeconomic dataset distributed through the `statsmodels` library. The dataset documentation indicates that the indicators were compiled primarily from the Federal Reserve Bank of St. Louis (FRED) and the U.S. Bureau of Labor Statistics [8, 17]. This data source is appropriate for the present study because it is public, stable, and easily reproducible, which supports later verification and replication by other researchers.

The dependent variable is next-quarter real consumer spending, operationalized as the one-step-ahead value of `realcons`. This target is suitable for a business paper because it captures aggregate consumer demand

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conditions that are directly relevant to revenue expectations, capacity planning, and market monitoring. The explanatory variables are one-period lagged values of real consumer spending, real GDP, real disposable personal income, real private investment, unemployment, inflation, and the Treasury bill rate. Together, these indicators represent demand momentum, macroeconomic activity, purchasing capacity, business confidence, labor-market conditions, price pressure, and monetary conditions.

Only lagged predictors are used in order to preserve forecasting realism. This means that each prediction is generated using information that would have been available to managers at the time of decision-making. The final modeling sample is created after applying the lag transformation and defining the next-quarter target.

Table 2: Variables used in the forecasting framework

Variable	Role	Business interpretation
`target_next_realcons`	Dependent	Next-quarter proxy for aggregate consumer demand.
`realcons_lag1`	Independent	Demand momentum and spending persistence.
`realgdp_lag1`	Independent	Overall economic activity and output conditions.
`realdpi_lag1`	Independent	Consumer purchasing capacity through disposable income.
`realinv_lag1`	Independent	Business investment climate and broader confidence conditions.
`unemp_lag1`	Independent	Labor-market pressure affecting expected demand.
`infl_lag1`	Independent	Price pressure and potential erosion of purchasing power.
`tbilrate_lag1`	Independent	Short-term financing and monetary conditions.

4.2. Forecasting design and model comparison

The study adopts a one-step-ahead forecasting design with a chronological 80:20 split between training and test observations. This is critical because random shuffling would leak future information into the model development stage and would therefore misrepresent forecasting performance. Figure 2 shows the split used in the experiment.

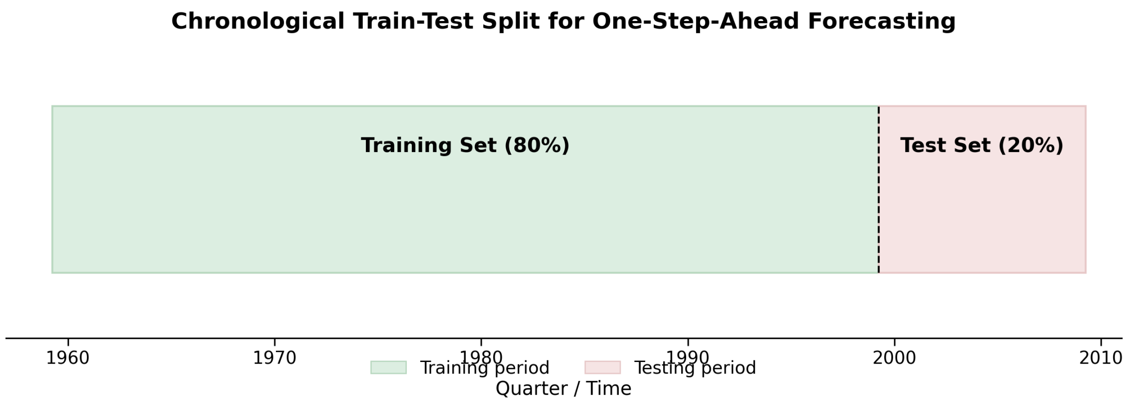

Figure 2: Chronological train-test split used for one-step-ahead forecasting

Four models are evaluated. Ordinary least squares (OLS) provides a transparent benchmark with straightforward economic interpretation. Ridge regression is included as a regularized linear alternative that may improve stability in the presence of collinearity. Random forest and gradient boosting represent two widely used machine-learning approaches capable of capturing more complex nonlinear relationships. Their inclusion allows the paper to test whether additional flexibility leads to superior out-of-sample performance in this business setting.

Forecasting accuracy is evaluated using mean absolute error (MAE), root mean squared error (RMSE), and out-of-sample R^2. These metrics provide complementary views of model quality by showing average absolute error, sensitivity to larger deviations, and overall explanatory strength on unseen data. The reproducible Python code used for all analyses is included in the package accompanying this manuscript.

4.3. Descriptive statistics

Table 3 presents descriptive statistics for the variables used in the forecasting exercise. The variables display substantial variation over time, which is expected given the multi-decade macroeconomic span of the dataset. Such variability is analytically useful because it allows the models to learn relationships across different phases of the economic cycle.

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Table 3: Descriptive statistics of the modeling dataset

Variable	Mean	Std. dev.	Min	Max
target_next_realcons	4856.19	2303.85	1751.80	9363.60
realcons_lag1	4781.54	2282.50	1707.40	9363.60
realgdp_lag1	7164.21	3179.35	2710.35	13415.27
realdpi_lag1	5263.29	2388.40	1886.90	10059.00
realinv_lag1	1008.30	586.21	259.76	2264.72
unemp_lag1	5.85	1.42	3.40	10.70
infl_lag1	3.97	3.27	-8.79	14.62
tbilrate_lag1	5.36	2.77	0.12	15.33

5. Results

5.1. Forecasting performance

The main forecasting results are presented in Table 4. The OLS model achieved the strongest out-of-sample performance with MAE = 61.34, RMSE = 86.51, and R^2 = 0.9825. Ridge regression performed almost identically, which suggests that the linear signal in the data is both strong and stable. By contrast, the tree-based models produced much larger errors and negative out-of-sample R^2 values, indicating poor generalization on the held-out period.

Table 4: Out-of-sample performance comparison

Model	MAE	RMSE	R^2
Ordinary least squares	61.34	86.51	0.9825
Ridge regression	61.61	86.77	0.9824
Random forest	1550.84	1694.80	-5.7168
Gradient boosting	1539.40	1697.53	-5.7385

Figure 3 shows the actual and OLS-predicted values over the test period. The close fit reinforces the conclusion that a parsimonious linear model is sufficient to capture much of the short-term dynamics in the target variable. Figure 4 and Figure 5 compare model errors across the four approaches.

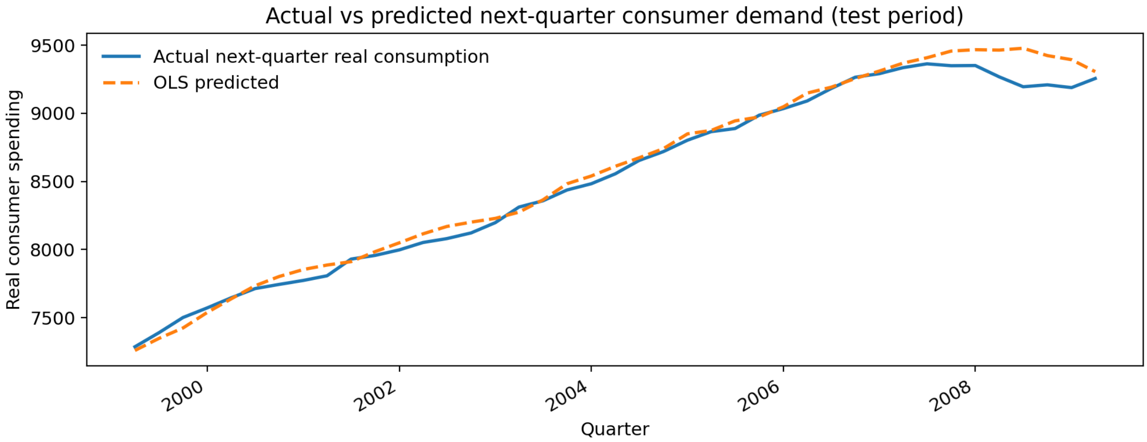

Figure 3: Actual versus OLS-predicted next-quarter consumer demand in the test period

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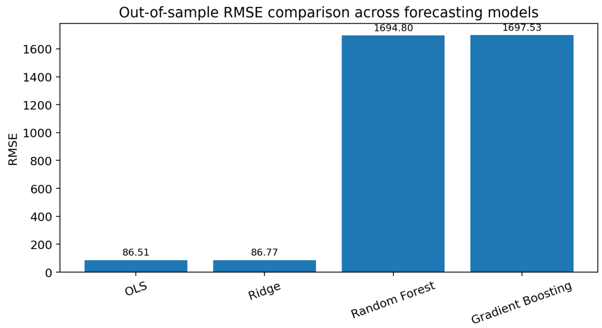

Figure 4: RMSE comparison

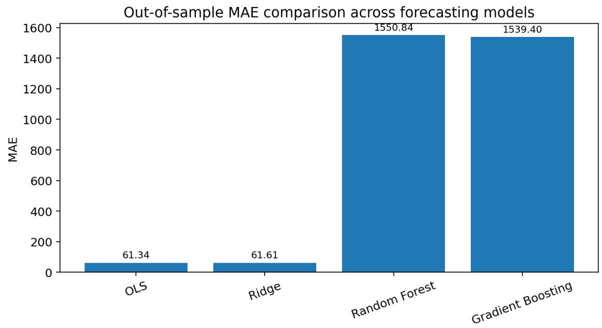

Figure 5: MAE comparison

These results provide direct support for H1 and H2. H1 is supported because the lagged macroeconomic indicators clearly contain enough predictive information to generate very strong out-of-sample performance in the linear models. H2 is also supported because the interpretable regression-based approaches performed better than the more complex machine-learning alternatives in this forecasting environment.

5.2. Coefficient interpretation and driver analysis

The OLS coefficient estimates provide an additional layer of managerial insight, which is precisely why this model is valuable in a BI setting. Table 5 reports the coefficient estimates and p-values. Lagged real consumption, lagged disposable income, and lagged real investment all have positive and statistically significant effects, suggesting that consumer demand persistence, purchasing power, and broader economic momentum are supportive of future spending. Inflation and short-term interest rates carry negative and statistically significant coefficients, which is consistent with the expectation that higher price pressure and tighter financing conditions can weaken future demand.

Table 5: OLS coefficient estimates for lagged macroeconomic drivers

Variable	Coefficient	p-value
realcons_lag1	0.7344	0.0000
realgdp_lag1	0.0189	0.7446
realdpi_lag1	0.1878	0.0005
realinv_lag1	0.2246	0.0000
unemp_lag1	10.3353	0.0009
infl_lag1	-4.0481	0.0001
tbilrate_lag1	-8.6527	0.0000

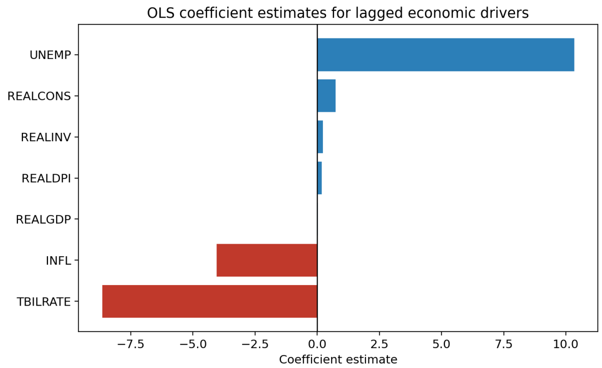

Figure 6: OLS coefficient profile

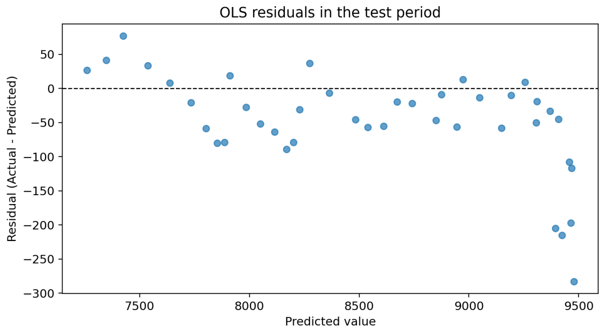

Figure 7: OLS residual pattern in the test period

The coefficient profile in Figure 6 visualizes the directional contribution of the main drivers, while Figure 7 shows that the residuals remain centered around zero without an obvious directional drift in the test period. From a business viewpoint, this matters because the model not only predicts well; it also provides a coherent narrative about which external signals are strengthening or weakening expected demand. This evidence supports H3 in the sense that the main macroeconomic drivers have meaningful and statistically significant predictive relationships with future demand.

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5.3. Expanded interpretation of the empirical contribution

The empirical contribution of the study extends beyond raw accuracy. First, the results show that public macroeconomic signals can be translated into an operationally useful BI artifact. Managers can, in principle, update the model periodically and use it as a forward-looking layer in dashboards that complement internal reporting. This is a stronger contribution than a conventional forecasting exercise because it demonstrates how external intelligence can be systematically transformed into business planning support.

Second, the strong performance of OLS and ridge regression offers an important practical message to managers and reviewers of business journals. In many managerial contexts, decision support systems are adopted not only because they are accurate but also because they are easy to interpret, justify, and communicate across functional boundaries. The present findings show that it is possible to preserve interpretability without sacrificing performance in this setting. This substantially strengthens the practical relevance of the study.

Third, the poor performance of the two tree-based models provides a cautionary note. It suggests that greater model complexity is not inherently superior in small to moderate macroeconomic samples where the signal is relatively smooth and strongly autocorrelated. This contributes to the current conversation in BI and analytics research by reinforcing the principle of methodological fit: the most suitable model is the one that aligns with both the data structure and the managerial purpose.

6. Discussion

6.1. Theoretical contribution

The study contributes to the BI and business analytics literature in several ways. The first contribution lies in demonstrating that public macroeconomic data can serve as a legitimate external intelligence layer within a BI architecture. Much of the recent BI literature emphasizes adoption factors, organizational capabilities, or conceptual differentiation between BI and BA [9, 11, 15]. The present paper complements this stream by showing how a transparent predictive workflow can be operationalized with fully reproducible public data. This moves the discussion from "whether BI matters" to "how BI can be instantiated as a concrete decision-support artifact."

A second theoretical contribution concerns the relationship between explainability and predictive performance. Recent research increasingly highlights the promise of AI-enhanced BI and advanced predictive analytics [1, 13]. However, the present findings indicate that explainable linear models can remain highly competitive, and in this case superior, within a realistic business forecasting environment. This result adds nuance to the literature by suggesting that the path from more advanced analytics to more business value is not automatic. In some contexts, parsimonious and interpretable models may provide stronger value because they align more closely with both the data structure and managerial needs.

A third contribution is conceptual. The framework developed in this paper links external macroeconomic indicators, forecasting models, dashboard interpretation, and managerial action in one integrated chain. This is important because BI value emerges when these elements are connected. The paper therefore contributes a managerial-process perspective rather than a narrow model-development perspective. Such a perspective fits recent calls for stronger integration between analytics capability, decision processes, and organizational outcomes [6, 16, 19].

6.2. Managerial implications

The managerial implications of the findings are substantial. First, the proposed framework offers firms a low-cost path for enriching their planning systems with external demand signals. Organizations that do not have sophisticated customer-level predictive infrastructures can still use public macroeconomic indicators as a systematic input into planning dashboards. This is especially relevant for SMEs, emerging-market firms, and institutions with limited analytics budgets.

Second, the coefficient-level insights provide managers with actionable narrative intelligence. For example, if inflation rises while disposable income weakens, the model's output can be interpreted as a warning of softer next-quarter demand. If investment and income strengthen, the model can signal improved demand conditions. Such interpretations can inform purchasing decisions, sales target setting, budget revisions, and staffing plans. In practice, this means the framework supports not just prediction but also coordinated managerial sensemaking.

Third, the study has implications for analytics governance. Organizations often assume that more complex machine-learning models are inherently superior and therefore more desirable. The present findings suggest a more disciplined selection logic. Managers should prioritize the model that best balances accuracy, transparency, operational fit, and implementation feasibility. In many BI settings, especially where models must be discussed in meetings and embedded in regular planning routines, explainability can be a strategic advantage rather than a limitation.

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Fourth, the study informs dashboard design. A useful BI dashboard should not only display a forecast value; it should also present the main underlying drivers and their directional effects. The framework proposed here lends itself naturally to such a design. A quarterly executive dashboard could include the forecasted next-quarter demand level, a trend view, and indicator panels for disposable income, inflation, unemployment, investment, and short-term rates. This would allow managers to move from passive reporting to more anticipatory planning.

6.3. Why the contribution is new and relevant

The study's novelty does not come from inventing a new algorithm. Instead, it comes from combining reproducibility, external-signal intelligence, explainability, and managerial interpretation within one coherent business-paper design. This combination is still relatively uncommon in BI-oriented journal submissions, where studies often emphasize either adoption models or technically advanced forecasting methods. By contrast, the present paper is intentionally positioned in the middle ground: rigorous enough to be empirically credible, but also written and designed for business readers concerned with decision quality and implementation relevance.

The paper is also timely. Recent literature shows growing organizational interest in predictive analytics, AI-enabled BI, and data-driven cultures, but managerial practice still faces recurring obstacles around trust, interpretability, and capability constraints. The current study speaks directly to these issues by showing that a transparent public-data forecasting layer can produce strong results and meaningful managerial insights without requiring opaque modeling infrastructure. In this sense, the paper contributes not only a method but also a pragmatic philosophy of BI design.

7. Conclusion

The present paper has created and tested a business intelligence system that can be used to predict the short-term consumer demand based on the public macroeconomic indicators. The study made forecasting as a BI-enabled decision-support feature as opposed to a technical modeling procedure by forecasting next-quarter real consumer spending based on lagged macroeconomic variables. The empirical findings indicated that regression based models particularly OLS performed the best out of sample and significantly better than the more complicated tree based machine-learning options.

The research adds value to the literature as it builds on recent literature on the BI, business analytics, and predictive decision support using a replicable empirical framework. It also adds to practice through demonstrating how external, publicly available data may be transformed into low-cost managerial intelligence that can be used to display in dashboards, budgeting, and operating readiness decisions. The findings suggest that explainable models are still very useful in the business environment since they can provide good predictive power as well as economic explanations.

Similar to any empirical research, the paper is limited. It is analyzed in a macro level instead of firm or product level, making it less specific to a particular business. The national context is confined to the environment of the U.S. macroeconomics, and the target variable is aggregate consumer demand, but not category- or customer-level demand. The framework can be extended in future studies through the use of industry specific sales series, firm level internal data, or cross country comparative setting. The future of BI-oriented forecasting research could also be in hybrid models that utilize internal and external signals to make predictions.

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