Advanced Decision Frameworks for Improving Sales Forecasting, Demand Planning and Business Performance in Saudi Automotive Enterprises.

Abstract

Vehicle distributors, dealer groups and aftersales businesses in Saudi Arabia commit stock, staff and capital months ahead of demand, so the quality of their sales forecasts and of the planning decisions built on them shapes service, inventory and profit. This paper proposes a decision framework that links sales forecasting, demand planning and sales and operations planning (S&OP) to business performance in Saudi automotive enterprises. The framework is grounded in an integrative review of 30 journal studies, all peer reviewed and published from 2020 to 2025. The two anchor studies are a support vector regression model for monthly automobile sales and a review of 292 publications on empirical and theoretical perspectives in S&OP. Studies of vehicle sales show that adding online search, review and opinion data and macroeconomic and promotional factors to sales histories improved accuracy in the reported cases, and that new products and product hierarchies need dedicated methods. Behavioural studies show that judgemental adjustments improve forecasts for only about half of items, that planners anchor on service levels and promotional uplifts, and that the way judgement is combined with algorithms matters. S&OP studies associate culture, behaviour, process efficiency and adaptive design with performance, although links to financial results are weaker than links to sales and delivery performance. Saudi evidence highlights market orientation, aftersales customer experience and a changing vehicle mix. The framework has four parts: demand intelligence, governed judgement, an adaptive S&OP decision cycle and a performance linkage system. No primary data were collected; the framework is assessed analytically against the evidence, and an evaluation design for Saudi firms is outlined.

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1. Introduction

Automotive enterprises plan far ahead of the sale. Importers and distributors order vehicles and parts on long lead times, dealer groups set targets and staffing for showrooms and workshops, and aftersales businesses decide which services and promotions to offer. Each of these decisions

depends on a view of future demand, and errors are costly in both directions: stock that does not sell ties up capital, while shortages lose customers to competitors. Vehicle sales respond to the market and the external environment, and accurate prediction helps dealers adjust their marketing plans (Qu et al., 2022).

Forecasting is only part of the problem. Forecasts are turned into plans through human judgement, meetings and trade-offs between sales, operations and finance. Research on judgemental forecasting shows that planners often adjust statistical forecasts and that these adjustments do not reliably add value (Fildes et al., 2025). Research on S&OP, the tactical process that brings demand and supply plans together, has grown rapidly; a review of 292 publications identified S&OP and performance, S&OP implementation and the contextualisation of S&OP designs as its main research streams (Kreuter et al., 2022). Yet the link from better forecasts and plans to business performance is rarely traced end to end.

Saudi Arabia adds specific conditions. The automotive industry has been discussed as a source of employment and investment, with import and export conditions affecting trade volume and jobs (Yusuf & Nasrulddin, 2021). The 2017 decree allowing women to drive was followed by stronger effects of market orientation on the performance of official car dealerships (Zouaoui & Zouaoui, 2022), and attitudes towards electric vehicles depend on factors such as safety and economic value (Habib et al., 2024). Such shifts make past sales a less reliable guide and raise the value of disciplined planning.

This paper develops a decision framework for improving sales forecasting, demand planning and business performance in Saudi automotive enterprises. It concentrates on vehicle and service sales, planning processes and performance measurement, and does not address spare parts inventory control, which raises different problems of intermittent demand. The remainder of the paper sets out the study's aims, describes the method, reviews the evidence in three strands, interprets it for Saudi enterprises, and presents and evaluates the framework.

2. Aim, Objectives and Guiding Questions of the Study

The study sets out to design decision rules and processes that tie forecasts, demand plans and S&OP decisions to measurable results for Saudi automotive firms. Four objectives follow: (1) to review evidence on forecasting methods and data for automotive sales; (2) to examine how

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human judgement affects forecasts and demand plans and how it can be governed; (3) to assess what is known about S&OP design and its relationship with performance; and (4) to combine the findings in a framework suited to the Saudi automotive context and evaluate it analytically.

Three questions guide the work. RQ1: Which forecasting methods and data sources improve the accuracy of automotive sales forecasts, and under what conditions? RQ2: How should judgement and S&OP processes be designed so that forecasts become sound demand plans? RQ3: How can forecasting, planning and performance measurement be combined into a decision framework for Saudi automotive enterprises?

3. Research Approach

The paper follows a design-oriented review. An integrative literature review gathered evidence across forecasting, behavioural operations and S&OP research, and a design step synthesised the evidence into a framework. Design science was chosen because the intended contribution is an artefact for practice, and because S&OP researchers have recommended this approach to bring practitioners into academic research (Kreuter et al., 2022).

The searches, run in November 2026, used a bibliographic database together with a scholarly metadata index. Search terms combined automobile or vehicle sales forecasting, demand planning, judgemental adjustment, forecast value added, algorithm aversion, sales and operations planning, forecast reconciliation and Saudi automotive sector. Eligible studies were English-language journal articles that had passed peer review, with its final publication year in the range 2020–2025, and had to report a method, empirical findings or a structured review relevant to sales forecasting, demand planning, S&OP or automotive business performance. Conference papers, practitioner articles and items without an accessible abstract were left out.

Qu et al. (2022), who forecast monthly automobile sales with support vector regression optimised by the grey wolf algorithm, and Kreuter et al. (2022), who reviewed empirical and theoretical perspectives in S&OP, served as anchor studies. Of the 30 studies retained, ten concern forecasting methods, data and accuracy measurement, seven deal with judgement in forecasting and demand planning, seven with S&OP design and performance, one with the integration of forecasting and inventory decisions, and five with the Saudi automotive context.

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For each study, the setting, data, method and reported findings were extracted, and each claim made in this paper was compared with the source. Numerical results are given as the studies report them and were not recalculated. The framework was evaluated analytically, by mapping each component to its evidence and by checking it against the conditions reported for Saudi automotive firms, and a design for empirical evaluation is proposed.

4. Forecasting Automotive Sales: Methods and Data

Automotive sales are difficult to forecast because they are non-stationary, nonlinear and affected by external factors as well as by their own history (Zhang et al., 2024). Qu et al. (2022) used grey correlation analysis to select the factors affecting sales and then applied a support vector regression model, tuned by the grey wolf optimiser, to monthly sales of two car models in China; it achieved the best mean absolute percentage error and root-mean-square error among the five methods compared. Zhang et al. (2024) combined a trend extrapolation model with a gradient-boosting model of 31 features covering dates, the macroeconomy and promotions, and found that a weighted-average combination performed best for data from three brands.

External data extend what a forecast can see. Zhang, Tian, and Fan (2022) converted online reviews into sentiment indices, added lagged search engine data and reported improved accuracy for the monthly sales of 14 automobile models. For intelligent vehicles, online public opinion and search index data improved prediction accuracy, opinion from key opinion leaders contributed more than that of the general public, and a long short-term memory network improved accuracy further (Zhang, Xu, et al., 2022). An extended Bass diffusion model that used online reviews, search traffic and macroeconomic data predicted automobile product sales more accurately than the traditional version, with macroeconomic data contributing most (Zhang et al., 2020). A survey of big data analytics for supply chain demand forecasting classified the methods used into time series, clustering, nearest-neighbour, neural network, regression and support vector approaches (Seyedan & Mafakheri, 2020).

New models and product hierarchies need their own treatment. For newly introduced products without sales history, a method that clusters demand patterns of earlier products and predicts quantiles of total demand from product characteristics gave the most accurate predictions among the benchmarks and potential inventory savings of around 15% (van Steenbergen & Mes, 2020). Automotive sales also form hierarchies, from brand to model, variant and region. Reconciliation

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methods make forecasts coherent across such hierarchies and can improve accuracy (Athanasopoulos et al., 2024), and a deep neural network that learns how to distribute top-level forecasts to lower levels increased average accuracy across a hierarchy of sales data (Mancuso et al., 2021).

How accuracy is measured also matters, though perhaps less than is often assumed. A large empirical study found only small discrepancies between error measures, especially within the same category of percentage, relative or scaled measures (Koutsandreas et al., 2022). For practice, this suggests choosing a small set of measures that are easy to communicate and applying them consistently, rather than debating the perfect metric.

In answer to RQ1, the evidence favours models that combine sales history with external signals, such as search, reviews, opinion, macroeconomic and promotional data, and that are combined or tuned rather than used singly. Most of this evidence comes from Chinese markets and from comparisons on a few brands or models, so gains should be expected to vary. New models require attribute-based methods, and forecasts at different levels should be reconciled. Table 1 summarises the evidence.

Table 1. Selected evidence on forecasting automotive and new-product sales (findings as stated in the original studies)

Study	Setting and data	Approach	Reported finding
Qu et al. (2022)	Monthly sales of two car models, China	Grey correlation factor selection; SVR tuned by grey wolf optimiser	Best MAPE and RMSE of five methods compared
Zhang et al. (2024)	Sales of three brands; 31 external features	SARIMA and polynomial trend with gradient boosting; combinations	Weighted-average combination performed best
Zhang, Tian, and Fan (2022)	Monthly sales of 14 automobile models	Review sentiment and search data with a neural network	Improved accuracy with good robustness
Zhang, Xu, et al. (2022)	Intelligent vehicle sales	Public opinion and search index; LSTM	Opinion and search data improved accuracy
Zhang et al. (2020)	Automobile product sales	Bass model with reviews, search and macroeconomic data	More accurate than traditional Bass model
van Steenbergen and Mes (2020)	New products, several companies	Clustering and quantile regression forests	Most accurate of benchmarks; about 15% potential inventory savings
Mancuso et al. (2021)	Hierarchical sales and electricity data	Neural network disaggregation of top-level forecasts	Higher average accuracy across the hierarchy

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5. Judgement in Forecasting and Demand Planning

Statistical forecasts are rarely used as they come. Across around 147,000 forecasts from six studies, bias and accuracy improved after adjustment in only slightly more than half of the stock keeping units; positive adjustments were more likely to worsen performance, while negative adjustments, especially large ones, usually helped (Fildes et al., 2025). The same study found weak evidence that forecasters used information unavailable to the algorithm, and showed that a debiasing procedure applied to adjusted forecasts improved performance. In experiments built on a UK retailer case, forecasters adjusting promotional forecasts anchored on the current statistical forecast and the most recent promotional uplift, and when a promotional model was shown they tended to misread contextual information and over-adjust (Sroginis et al., 2023).

Judgement can also be useful. In experiments, forecasters who selected among statistical models outperformed the average of the models, and their adjusted forecasts were more influenced by better models as they gained experience (De Baets & Harvey, 2020). The method of integration matters: a laboratory and field study found that letting the algorithm learn from human judgement through iterative weighting was more accurate than judgemental adjustment, forecast combination and several other established integration methods (Brau et al., 2023). Acceptance of algorithms is a further issue; in an experiment with 1,840 participants, time pressure reduced algorithm aversion, while goals and data input rights did not (Jung & Seiter, 2021).

Two findings speak directly to the confusion between forecasts and plans. Forecasters factored service levels into demand forecasts even when told to predict the most likely demand and rewarded for minimising error (Fahimnia et al., 2023). In a manufacturing firm, disaggregating the forecast by sources of demand reduced absolute forecast error and finished goods inventory without more costly production plan changes, although positive bias persisted for products with scarce production capacity, where sales managers had incentives to inflate forecasts (Brüggen et al., 2021). For automotive enterprises, where sales targets and allocation of scarce models are sensitive, these results caution against letting targets or service goals leak into the forecast.

Together, these studies suggest that judgement should be governed rather than banned: adjustments should be documented with reasons, their value tracked, upward adjustments scrutinised, service targets applied after the forecast rather than within it, and incentives that reward inflated forecasts removed.

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6. S&OP Design and Business Performance

S&OP is the process in which demand and supply plans are reconciled and decisions are taken across functions. Evidence on its performance effects is growing but mixed. In a survey of Danish manufacturers with an S&OP process, key behavioural indicators were positively related to S&OP efficiency, and process efficiency was positively related to sales and operational performance (Stentoft et al., 2022). An earlier survey of 156 Danish manufacturers, using secondary performance data, found that the perceived relevance of S&OP was related to sales performance in terms of customers and delivery but not to operational or financial performance (Stentoft et al., 2020).

Culture and alignment matter. A global survey of S&OP practitioners found that a strong S&OP culture improved coordination outcomes mainly through strategic alignment and information acquisition and processing, while it could also suppress supply chain performance through the procedure and schedule mechanism (Goh & Eldridge, 2024). A review using contingency theory found that strategic alignment in S&OP is difficult to achieve in practice and argued for a shift in mindset from control to growth (Shanahan et al., 2025).

Design must also adapt. Seven process-industry organisations designed their S&OP around their main risks and used crisis meetings and temporary design changes to deal with emerging risks (Dittfeld et al., 2021). A longitudinal case of a Danish manufacturer found that adaptive S&OP design was central to performance and resilience, that expanding S&OP scope set off interdependent changes, and that including new products required flexibility in several design parameters (Wu et al., 2025). Finally, forecasting and inventory decisions are often studied separately; a structured review identified four levels of integration between them and argued that greater integration adds realism but also complexity (Goltsos et al., 2022).

In answer to RQ2, sound demand plans require governed judgement and an S&OP process that is efficient, aligned with strategy and able to change its design when risks or the product range change. Performance effects appear most clearly in sales and delivery outcomes, so firms should not expect S&OP alone to produce immediate financial gains.

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7. The Saudi Automotive Context

Saudi evidence on automotive enterprises is limited but relevant. Among managers and executives of official car dealerships, market orientation had a positive effect on company performance both before and after the women's driving decree; before it, only customer orientation and inter-functional coordination mattered, while afterwards competitor orientation also did, which the authors attributed to intensified competition (Zouaoui & Zouaoui, 2022). Inter-functional coordination is precisely what S&OP seeks to institutionalise.

Aftersales is a second source of evidence. A survey of 395 customers in the Saudi automotive aftersales sector found that service quality and price perception significantly improved customer experience and engagement, with experience mediating these relationships (Amro, Rehman, & Ali, 2025). Another study of the same sector found that customer-centric culture influenced engagement indirectly through customer experience and recommended data-driven management aligned with Vision 2030 (Amro, Rehman, Ullah, et al., 2025). For planning, these findings imply that service demand forecasts should be linked to experience and engagement measures, not only to volumes.

The market itself is changing. Consumer attitudes towards electric vehicles in Saudi Arabia were shaped significantly by product variety, operating cost, economic value, social influence and safety rating, whereas range anxiety and charging infrastructure were less significant (Habib et al., 2024). Discussion of the sector has also linked import and export conditions and foreign investment to growth and employment (Yusuf & Nasrulddin, 2021). New powertrains and models therefore enter a market with limited sales history for them, which strengthens the case for attribute-based forecasting of new products and for S&OP designs that can absorb new products.

8. A Forecast-to-Performance Decision Framework

Figure 1 presents the proposed framework. It has four connected components: demand intelligence, governed judgement, an adaptive S&OP decision cycle and a performance linkage system. Outcomes from the performance linkage system feed back into the other components, so that the framework learns which forecasts, adjustments and decisions add value.

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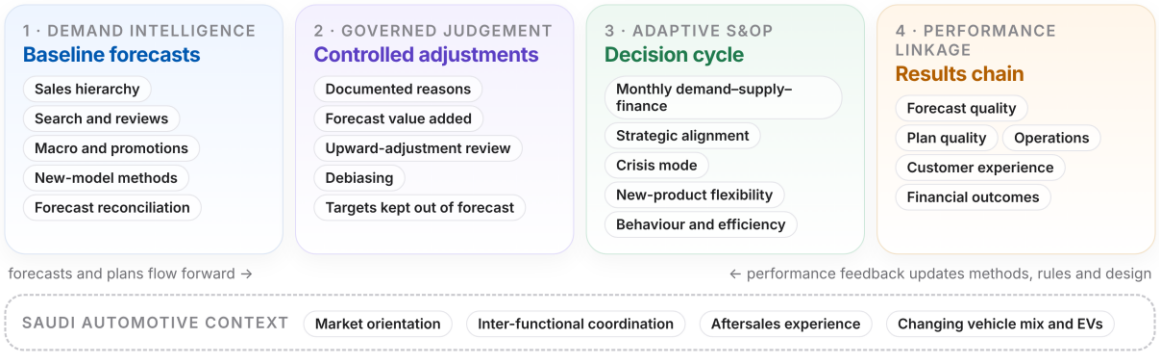


Figure 1. Proposed forecast-to-performance decision framework for Saudi automotive enterprises.

Demand intelligence produces baseline forecasts. It organises sales data in a hierarchy of brand, model, variant, region and channel, adds external signals such as search, review, opinion, macroeconomic and promotional data where they exist (Zhang, Tian, & Fan, 2022; Zhang et al., 2024), uses attribute-based methods for new models (van Steenbergen & Mes, 2020) and reconciles forecasts across levels (Athanasopoulos et al., 2024; Mancuso et al., 2021). Accuracy is tracked with a small, stable set of measures (Koutsandreas et al., 2022).

Governed judgement controls how people change forecasts. Table 2 sets out its decision rules. Adjustments are allowed when planners have information the model lacks, must be documented and are monitored through forecast value added; upward adjustments receive extra review and debiasing is applied where bias persists (Fildes et al., 2025). Service targets and sales targets are kept out of the forecast and applied in the plan (Brüggen et al., 2021; Fahimnia et al., 2023), and the method for combining judgement with models is chosen deliberately (Brau et al., 2023).

Table 2. Decision rules for governed judgement in the proposed framework

Decision point	Rule	Rationale	Evidence base
Whether to adjust	Adjust only for information the model lacks; record the reason	Adjustments help for only about half of items	Fildes et al. (2025)
Direction and size	Review upward adjustments more strictly; debias persistent bias	Positive adjustments more often worsen accuracy	Fildes et al. (2025)
Targets and service levels	Keep sales and service targets out of the forecast; apply them in the plan	Service levels and incentives bias forecasts	Fahimnia et al. (2023); Brüggen et al. (2021)

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Decision point	Rule	Rationale	Evidence base
Promotions and events	Show baseline and past promotion history, not only last uplift	Planners anchor on recent uplift and over-adjust	Sroginis et al. (2023)
Method selection	Let planners choose among models with visible track records	Experienced planners select and follow better models	De Baets and Harvey (2020)
Combining judgement and models	Choose the integration method deliberately and test it	Accuracy depends on the integration method	Brau et al. (2023)
Acceptance of models	Address algorithm aversion explicitly in planning routines	Time pressure reduced aversion in experiments	Jung and Seiter (2021)

The adaptive S&OP decision cycle turns forecasts into plans. A monthly cycle reviews demand, supply and financial plans, links them to strategy and records decisions (Shanahan et al., 2025). The design is reviewed when risks, scope or the product range change, for example when electric models are introduced, and a crisis mode is available for disruptions (Dittfeld et al., 2021; Wu et al., 2025). Attention to behaviour and process efficiency is built into the cycle (Stentoft et al., 2022), and procedures and schedules are kept flexible, since they can transmit a suppressing effect on performance (Goh & Eldridge, 2024).

The performance linkage system connects planning to results through a chain of measures, shown in Figure 2: forecast quality, plan quality, operational outcomes, customer outcomes and financial outcomes. It reflects the finding that S&OP effects appear first in sales and delivery performance (Stentoft et al., 2020), includes the market orientation and customer experience measures found important in Saudi studies (Amro, Rehman, & Ali, 2025; Zouaoui & Zouaoui, 2022), and connects forecasting with stock decisions, as integration research recommends (Goltsos et al., 2022).

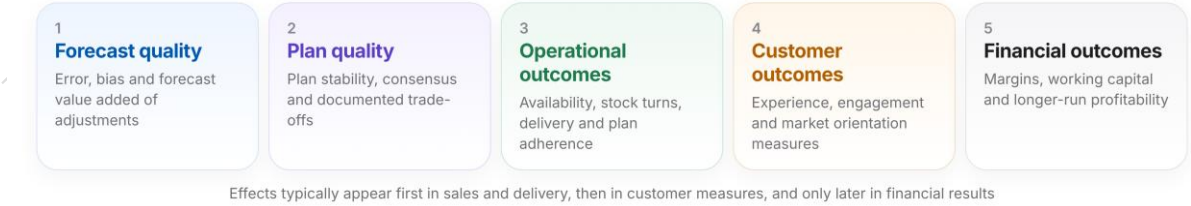


Figure 2. Performance linkage chain used in the proposed framework, from forecast quality to financial outcomes.

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9. Analytical Evaluation

Three evaluation checks were applied. First, each component was traced to evidence: demand intelligence to ten forecasting studies, governed judgement to seven behavioural studies, the S&OP cycle to seven S&OP studies and the performance linkage system to S&OP performance, integration and Saudi studies. No component depends on a single source. Second, the framework was checked against Saudi conditions: market orientation and inter-functional coordination are addressed in the S&OP cycle, aftersales experience in the performance measures, and the changing vehicle mix in new-product forecasting and adaptive design.

Third, the framework was checked for internal consistency with the evidence on limits. It does not assume that external data always help, because the reported gains come from specific markets and models; it does not assume that S&OP produces financial gains directly; and it does not remove judgement, because some studies show that judgement can add value when integrated well (Brau et al., 2023; De Baets & Harvey, 2020).

The framework has not been implemented, so its effects are unknown. An empirical evaluation could follow a stepped design in several Saudi dealer groups or distributors. A baseline period would record forecast error and bias, forecast value added of adjustments, plan stability, stock and availability measures, customer experience scores and financial ratios. The components would then be introduced in stages, beginning with governed judgement, which requires the least technology, and changes would be compared with the baseline and with sites not yet using the framework. Results should be reported in full, including where components did not help.

10. Discussion and Limitations

The review shows that the three bodies of research relevant to the title rarely meet. Forecasting studies of automotive sales measure accuracy but seldom follow forecasts into plans or results. Behavioural studies show how judgement changes forecasts but usually in laboratory or retail settings. S&OP studies examine performance but rarely measure forecast quality. The framework's contribution is to connect them in one decision structure and to make performance measurement part of the planning loop rather than an afterthought.

For Saudi automotive managers, three priorities follow. Governing judgemental adjustments and separating forecasts from targets are low-cost steps that the evidence supports. Investing in

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external data and advanced models is worthwhile mainly where history is short or the market is shifting, as with new powertrains. And S&OP should be built around inter-functional coordination and customer measures, which Saudi studies link to performance, with financial effects expected only over time.

The study has several limitations. The corpus of 30 articles, selected for coverage across strands, does not capture all relevant work. Most forecasting evidence comes from China and most S&OP evidence from Danish or global samples, so transfer to Saudi enterprises is uncertain. The Saudi studies concern market orientation, aftersales and electric vehicle attitudes rather than forecasting or S&OP directly, and no Saudi study of automotive demand planning was found. The evaluation is analytical, and the proposed empirical design has yet to be carried out.

11. Conclusion

Better forecasts improve business performance only when they become better plans and better decisions. Drawing on 30 studies, this paper has shown that external signals and combined models can improve automotive sales forecasts in the reported cases, that judgement adds value only under governance, and that S&OP design, culture and alignment are associated with sales and delivery performance more clearly than with financial results. For Saudi automotive enterprises facing a changing market, the proposed framework links demand intelligence, governed judgement, an adaptive S&OP cycle and a chain of performance measures. Testing it in Saudi dealer groups and distributors is the necessary next step.

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