SUPPLY CHAIN ANALYTICS

Advanced Decision Support Systems for Optimising Automotive Spare Parts Demand Forecasting and Inventory Management in Saudi Arabia

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Abstract

Automotive distributors, dealers and service networks in Saudi Arabia hold thousands of spare parts whose demand is sporadic, lumpy and often short of history, so that the same stock budget can produce both shortages and dead inventory. This paper develops a decision support system (DSS) framework for optimising spare parts demand forecasting and inventory management in the Saudi automotive after-market. The framework rests on an integrative review of 30 peer-reviewed studies that appeared in journals between 2020 and 2025. Its two anchors are a review of 148 studies on spare parts inventory management and a deep learning study of automobile spare parts demand that assessed both forecast accuracy and inventory performance. The evidence shows that no single forecasting method dominates: classical intermittent-demand methods remain competitive for some demand classes, while machine learning, transformer and combination methods tend to gain as demand becomes sparser or when external and reliability data are available. It also shows that accuracy gains matter only when they are translated into stock decisions, that the transition to optimised stock levels must itself be controlled, and that parts with no history or facing obsolescence need dedicated methods. Saudi evidence points to localisation of automotive production, a slow move towards electric vehicles and limited adoption of structured improvement methods in maintenance firms. The proposed DSS combines a data foundation, demand profiling and segmentation, a forecasting method library with automated selection, inventory optimisation, controlled policy transition, and monitoring with planner feedback. No new data were collected; the framework is evaluated by tracing each component to published evidence, and an evaluation protocol for Saudi pilots is proposed.

1 Introduction

Spare parts keep vehicles on the road. Dealers, distributors and independent workshops must stock parts for many models, model years and powertrains, and their customers expect a repair to be completed quickly. Spare parts are held as inventory precisely to reduce downtime and extend the life of products, and the right-to-repair movement has added pressure on manufacturers to keep parts available throughout a product's life cycle (Zhang et al., 2021). The difficulty is that most parts are sold rarely and irregularly. In the heavy-duty vehicle industry, for example, intermittent demand is common for spare parts, and its uncertainty challenges conventional forecasting models (Jiang et al., 2021), and in the automotive sector the empirical method of building lead-time demand distributions from history works reasonably well at low service requirements but struggles to reach high target service levels (Chandriah & Naraganahalli, 2021).

These problems have a particular shape in Saudi Arabia. The Kingdom is pursuing localisation of automotive manufacturing as part of Vision 2030, and a survey of 106 Saudi automobile companies found that larger firms were applying a localised production model built on Industry 4.0 more than

medium and smaller firms (Aljuaid et al., 2024). Electric vehicle uptake remains uncertain, since potential drivers ranked the lack of charging infrastructure and the extra load on the national grid as the most important barriers (Alotaibi et al., 2022). Both trends change the mix of parts that must be stocked. Meanwhile, the financial stakes of inventory are clear: across 78 listed Saudi manufacturers, higher inventory turnover was associated with higher profitability (Alnaim & Kouaib, 2023).

Research on spare parts forecasting is extensive, and a recent critical review traced its development over five decades and analysed quantitatively when particular methods should be preferred (Pinçe et al., 2021). Yet methods are rarely organised into a decision support system that a parts manager can use, and the link between forecasting, stocking and implementation is often treated piecemeal. This paper therefore asks how an advanced DSS should be designed to optimise spare parts forecasting and inventory decisions in Saudi automotive enterprises.

The paper makes three contributions. It synthesises recent evidence on intermittent demand forecasting and spare parts inventory control with a view to decisions rather than methods alone. It positions this evidence within the Saudi automotive context. It then proposes a DSS framework, with explicit decision rules for different demand segments, and outlines how future pilots could test it. No new data were collected, and no performance figures are claimed for the framework itself.

The remainder of the paper proceeds as follows. The aim, objectives and questions come first, followed by the method. Three sections then review forecasting evidence, the link from forecasts to stock decisions, and the Saudi context. The framework is presented next, followed by a discussion and the conclusion.

2 Purpose, objectives and research questions

The purpose of the study is to design a decision support system framework that improves the accuracy of spare parts demand forecasts and the quality of the inventory decisions based on them in Saudi automotive enterprises. The objectives are: (1) to establish which forecasting approaches suit which spare parts demand conditions; (2) to identify how forecasts should be converted into inventory policies and how policy changes should be implemented; (3) to identify contextual conditions in the Saudi automotive sector that the DSS must accommodate; and (4) to specify the components, decision rules and evaluation measures of a DSS that integrates these elements.

The study addresses three research questions. RQ1: Which forecasting approaches perform best for automotive and comparable spare parts under different demand conditions, according to recent evidence? RQ2: How should forecasting outputs be linked to inventory optimisation and implementation decisions? RQ3: What DSS architecture and decision rules can integrate these findings for Saudi automotive spare parts management, and how should the system be evaluated?

3 Review and design method

The study combines an integrative literature review with a design-oriented synthesis. An integrative review suits the topic because the relevant evidence comes from operations research, forecasting, machine learning, maintenance engineering and regional business studies, and because the goal is to build a framework rather than to estimate a single pooled effect.

The literature was searched in November 2026 through a scholarly metadata index. Search strings combined part and sector terms ("spare parts", "automotive aftermarket", "vehicle"), demand terms

("intermittent demand", "lumpy demand", "demand forecasting", "Croston"), decision terms ("inventory", "service level", "decision support", "classification") and context terms ("Saudi Arabia", "automotive industry", "Vision 2030"). Searches restricted to particular publishers' records and an open bibliographic index supplemented these. Eligible sources were English-language, peer-reviewed journal articles whose final publication year lay between 2020 and 2025, and had to provide methodological, empirical or contextual evidence on spare parts forecasting, spare parts inventory decisions or the Saudi automotive and maintenance setting. Conference proceedings, theses and items whose metadata could not be verified were excluded.

Two anchor studies framed the search. The first is a literature review of 148 papers on spare parts inventory management published between 2010 and 2020, which classifies the field by descriptive, predictive and prescriptive analytics and identifies gaps in demand pattern modelling and big data analytics (Zhang et al., 2021). The second applied recurrent neural networks with long short-term memory and a modified Adam optimiser to automobile spare parts demand and evaluated both forecast accuracy and inventory performance (Chandriah & Naraganahalli, 2021). The final corpus contains 30 articles: fifteen on forecasting methods for intermittent and lumpy demand, eight on inventory control, classification and decision support for spare parts, and seven on the automotive market and the Saudi context.

Findings were extracted in a structured form covering the setting, data, method and reported result, and each claim in the paper was checked against its source. The framework was derived by mapping recurring findings to DSS components and decision rules. Because the study is a synthesis, the framework is evaluated by traceability to evidence, not by new experiments; an evaluation protocol for empirical testing is proposed in Section 7.

4 Forecasting spare parts demand: what the evidence shows

The first lesson is that method choice should depend on demand characteristics. Intermittent demand is grouped into categories for better management, and guidance on method selection by category simplifies forecasting for practitioners (Kaya et al., 2020). The critical review by Pinçe et al. (2021) reaches a similar conclusion from a quantitative analysis of published studies: which method should be preferred depends on when and why it is applied. A DSS should therefore begin by profiling each part's demand rather than applying one method to the whole range.

The second lesson is that separating whether demand occurs from how much is demanded often helps. Using 516 daily demand series over three years from a European original automotive equipment manufacturer, a two-model approach found that global classification models were best at predicting demand occurrence, while simple exponential smoothing gave the best demand size forecasts (Rožanec et al., 2022). In the automotive after-sales business, a combined method that predicts occurrence with a classification model and non-zero quantities with a regression model, using internal and external data, improved classification accuracy and forecasting precision over other intermittent methods (Zhuang et al., 2022).

The third lesson is that machine learning helps most where demand is sparse and where additional information is available. For heavy-duty vehicle spare parts, an adaptive univariate support vector machine, benchmarked against a dozen established models and an enhanced neural network, delivered significantly more accurate forecasts and stronger inventory results for demand series that were not smooth, and it computed faster than basic support vector machines and neural networks (Jiang et al., 2021). In a test of 925 intermittent items from an airline spare parts provider, a

transformer network performed very well against Croston's method, the Syntetos–Boylan approximation and several neural networks; models performed similarly when sparsity was low, but the transformer's advantage grew with sparsity (Zhang et al., 2024). Recurrent networks with an optimised training algorithm produced minimal error for automobile spare parts compared with existing methods (Chandriah & Naraganahalli, 2021), and for safety-critical aviation parts with lumpy demand a neural network with a momentum term outperformed benchmark models and was expected to reduce dead inventory caused by human error in demand estimates (Shafi et al., 2023).

Data imbalance and data gaps are recurring problems. Because zero-demand periods vastly outnumber demand events, an ensemble that combined synthetic minority oversampling with focal loss reduced mean squared error by 47% and raised the area under the curve by 32% (Kenaka et al., 2025). Transfer learning can compensate for the limited information in a single series by learning from clusters of similar intermittent series, which improved stability and accuracy on after-sales data from two equipment manufacturers (Fan et al., 2023). Where point-of-sale data are missing for some customers, clustering customers with similar delivery patterns improved intermittent forecasts by up to 10% (Ducharme et al., 2024). Reliability and operating environment features also add predictive value: in military aircraft spare parts, random forests using managerial and reliability features outperformed other data mining techniques and conventional time series methods (Choi & Suh, 2020).

Two special cases need their own methods. New parts have little or no history. A framework that predicts the distance between demand profiles from attribute-wise comparisons of parts, tested on more than 28,000 parts from 131 sites, significantly improved forecasts for parts without demand history compared with alternative models (Caserta & D'Angelo, 2025). Parts that are becoming obsolete pose the opposite problem. Only two methods had been designed for intermittent demand with possible obsolescence, and both continue to predict non-zero demand indefinitely; exponential smoothing with linear decay reaches zero in finite time and performed well on real and synthetic data (Prestwich et al., 2021). For automotive ranges affected by model changes and electrification, both cases are routine rather than exceptional.

Finally, combining forecasts is a robust option. A feature-based framework for combining intermittent demand forecasts improved the accuracy of point and quantile forecasts on two real data sets and offered insights for inventory decisions (Li et al., 2023). Table 1 summarises the forecasting evidence. In answer to RQ1, no single method is best: classical intermittent methods remain useful benchmarks and are competitive for smoother demand, occurrence-size decomposition and combinations are robust across classes, machine learning and deep learning gain as sparsity rises and when external, reliability or cross-series information is available, and parts without history or facing obsolescence require dedicated methods.

Table 1. Selected evidence on spare parts demand forecasting (results as reported by each study)

Study	Setting and data	Approach	Reported finding
Rožanec et al. (2022)	516 daily series, automotive equipment manufacturer	Separate occurrence and size models	Global classifiers best for occurrence; exponential smoothing best for size
Zhuang et al. (2022)	Automotive after-sales data	Classification plus regression, internal and external data	Higher classification accuracy and precision than other intermittent methods

Study	Setting and data	Approach	Reported finding
Jiang et al. (2021)	Heavy-duty vehicle spare parts	Adaptive support vector machine vs 12 models	Better accuracy and inventory performance for non-smooth series
Chandriah and Naraganahalli (2021)	Automobile spare parts	Recurrent network with modified optimiser	Minimal error compared with existing methods
Zhang et al. (2024)	925 airline spare parts	Transformer vs Croston-type and neural methods	Advantage grows as sparsity increases
Kenaka et al. (2025)	Intermittent spare parts	Oversampling and focal loss ensemble	47% lower MSE; 32% higher AUC
Caserta and D'Angelo (2025)	Over 28,000 parts, 131 sites	Similarity of demand profiles	Better forecasts for parts without history
Prestwich et al. (2021)	Real and synthetic data	Exponential smoothing with linear decay	Forecasts reach zero in finite time under obsolescence
Li et al. (2023)	Two real data sets	Feature-based forecast combination	More accurate point and quantile forecasts

5 From forecasts to stock decisions

Forecasts create value only through the decisions they inform. Several studies make this link explicit. Jiang et al. (2021) and Chandriah and Naraganahalli (2021) evaluated inventory performance alongside accuracy, and in the automotive industry a multi-cost function approach that selects and adjusts a forecasting model for each part, combined with a negative binomial–Bernoulli distribution for stock control and an item-level safety stock calculation, significantly reduced safety stock while maintaining service levels (Sfiris & Koulouriotis, 2025). The same study introduced a prediction error cost metric oriented to stock-keeping units, underlining that accuracy measures should reflect the cost of errors at the part level.

Inventory policy design adds a second layer of decisions. One model computes lower and upper inventory bounds that balance holding costs against lost sales for intermittent demand, solved with genetic algorithms and particle swarm optimisation on seven test data sets (Yuna et al., 2023). Classification supports these choices when thousands of parts must be managed: a graph-based deep convolutional network achieved explainable multi-criteria spare parts classification and was presented as decision support for focusing on critical components and controlling inventory (Yang et al., 2021). Prognostic information can refine ordering further: a maintenance decision model that uses predictions of remaining useful life determines when to order and replace spare parts to minimise cost while maximising availability (Zhang et al., 2025). In automotive settings, production, sales and failure data for an engine control device were combined with Kaplan–Meier and Weibull models into a roadmap from raw data to predictive models for spare parts (Fragassa, 2024).

Sourcing options change the inventory problem. Combining additive and conventional manufacturing as dual sources achieved savings of more than 30% compared with the best single-sourcing option in an aviation case, even when additively produced parts were three times worse in reliability or unit cost (Knofius et al., 2021). This is relevant to Saudi Arabia, where additive manufacturing has been proposed for producing automobile parts locally to meet customers' particular needs more quickly and economically (Aljuaid et al., 2023).

Implementation is itself a decision problem. When a company introduced an improved spare parts inventory policy, stock increased quickly for parts with higher base stock levels but fell slowly for low-demand parts, so that inventory cost exceeded the budget substantially in the first months; phasing in base stock changes through an optimised transition improved fill rates quickly without exceeding the initial budget (Haubitz & Thonemann, 2021). A DSS that recommends new stock levels without managing the transition can therefore worsen performance in the short term.

In answer to RQ2, forecasts should feed item-level stock optimisation that uses cost-oriented error measures and demand distributions suited to intermittency, policies should be differentiated by part class and criticality, reliability and prognostic data should inform ordering where available, sourcing options such as additive manufacturing should be treated as decision variables, and the move from current to optimised stock levels should be planned and controlled.

6 The Saudi automotive aftermarket context

Four features of the Saudi context matter for DSS design. The first is industrial localisation. Saudi Arabia's automotive localisation model combines domestic manufacturing with Industry 4.0, and companies that applied it reported improvements in customer satisfaction through customisation and in revenue (Aljuaid et al., 2024). As local production and assembly grow, parts networks will need to integrate local and imported supply and to forecast demand for parts with short histories.

The second is the powertrain transition. In a survey of 698 potential drivers, barriers to electric vehicle adoption included charging infrastructure, the load on the national grid, battery safety and effectiveness at high temperatures, and the cost of purchase and maintenance (Alotaibi et al., 2022). An interpretive structural model of 17 factors placed purchase price, resale value and long-term savings, together with accessibility and urban planning, among the most influential drivers (Al-moshaogeh et al., 2025). The pace of transition is therefore uncertain, which argues for a DSS that monitors demand for both conventional and electric vehicle parts and handles obsolescence explicitly.

The third is organisational maturity. Among 77 practitioners in Saudi maintenance companies, 77.9% reported that their organisations had not yet implemented Lean Six Sigma, and comprehensive training, careful staff selection, awareness and a data-driven approach were identified as critical success factors (Alghuried et al., 2024). Structured, data-driven methods cannot be assumed to be in place, so a DSS must be usable by planners with mixed analytical skills and must support, rather than replace, their judgement.

The fourth is the business case. The positive association between inventory turnover and profitability among Saudi manufacturers (Alnaim & Kouaib, 2023) gives managers a financial rationale for better parts planning. At the same time, forecasting vehicle spare parts demand and price is hampered by scarce data and by pricing that does not follow normal value chain logic, and regression models proved insufficient for a hybrid vehicle case (Alalawin et al., 2021). Judgement remains common where formal methods are weak, as in performance-based logistics contracts for aircraft parts (Choi & Suh, 2020). These findings support a DSS that combines statistical and machine learning methods with structured planner input.

7 A decision support system framework for spare parts

Figure 1 presents the proposed DSS. It has six components arranged as a closed loop. The data foundation integrates sales and workshop demand histories, part master data, vehicle parc and age information, supersession and model-change records, supplier lead times and, where available, failure and reliability data. Integrating production, sales and failure data in this way follows the roadmap demonstrated for automotive components (Fragassa, 2024), and drawing on external and cross-customer data addresses the information gaps documented by Zhuang et al. (2022) and Ducharme et al. (2024).

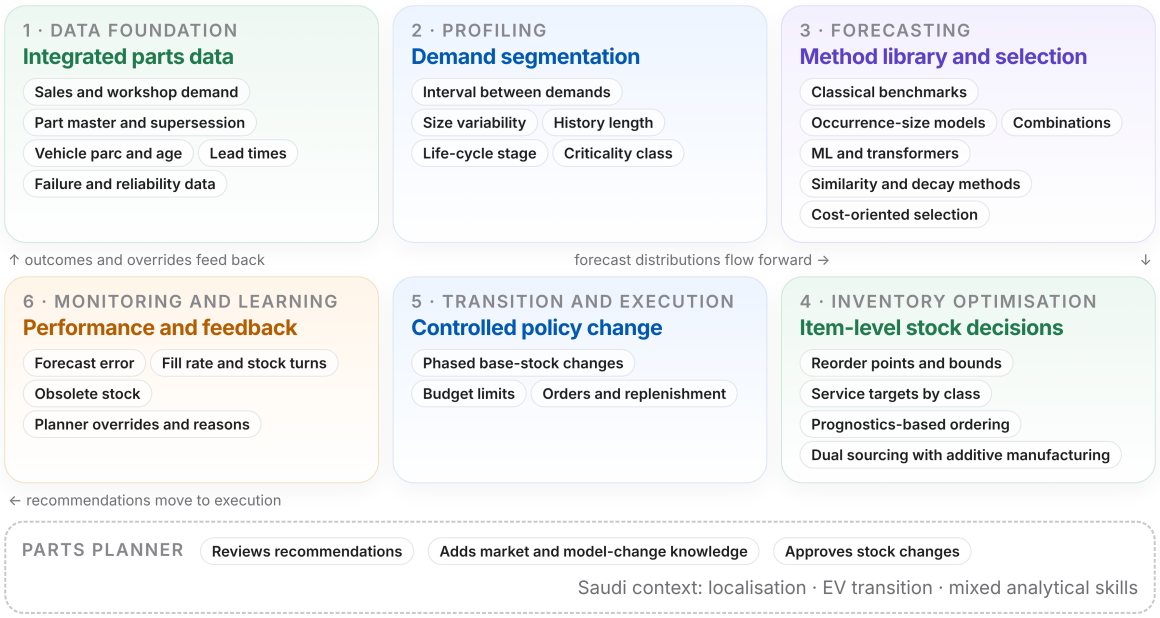

Figure 1. Proposed decision support system for automotive spare parts forecasting and inventory management

The demand profiling and segmentation component classifies each part by the average interval between demands, the variability of demand sizes, history length, life-cycle stage and criticality. Explainable multi-criteria classification of the kind developed by Yang et al. (2021) supports the criticality dimension, and segmentation by demand category follows the guidance of Kaya et al. (2020). Each segment is linked to a default set of candidate methods.

The forecasting method library contains classical intermittent-demand methods as benchmarks, occurrence-size models, combination methods, machine learning and deep learning models, similarity-based methods for parts without history and decay methods for obsolescence. Model selection is automated per part, using cost-oriented error measures rather than accuracy alone (Sfiris & Koulouriotis, 2025) and favouring combinations where no method is clearly superior (Li et al., 2023). More complex models are activated only where their advantage is expected to be material, for example in highly sparse series (Zhang et al., 2024) or where imbalance requires rebalancing techniques (Kenaka et al., 2025).

The inventory optimisation component converts forecast distributions into reorder points, base stock levels or inventory bounds for each part (Yuna et al., 2023), subject to service targets set by criticality class and to the overall budget. Where prognostic data exist, it schedules orders against predicted failures (Zhang et al., 2025), and it can evaluate dual sourcing with local additive manufacturing for

low-volume parts (Knofius et al., 2021). The policy transition and execution component phases in changes to stock levels so that budgets are respected while service improves (Haubitz & Thonemann, 2021). Finally, the monitoring and learning component tracks forecast errors, fill rates, stock turns and obsolete stock, records planner overrides with their reasons, and feeds results back to model selection and segmentation.

Table 2 sets out the decision rules that connect demand segments to forecasting and inventory choices, and Figure 2 shows the segment-to-method map that the DSS uses as its default configuration. These rules are starting points derived from the evidence; each organisation should recalibrate them on its own data.

Table 2. Default decision rules of the proposed DSS by demand segment

Demand segment	Forecasting approach	Inventory decision	Evidence base
Smoother, frequent demand	Classical methods and combinations as benchmarks	Standard reorder point by service class	Kaya et al. (2020); Li et al. (2023)
Intermittent, moderate sparsity	Occurrence-size models; combinations	Item-level safety stock from intermittent distributions	Rožanec et al. (2022); Sfiris and Koulouriotis (2025)
Highly sparse or lumpy	Machine learning or transformer models with imbalance handling	Inventory bounds balancing holding cost and lost sales	Zhang et al. (2024); Kenaka et al. (2025); Yuna et al. (2023)
Erratic or driver-dependent demand	Models using external, cross-series or reliability features	Prognostics-based ordering where data allow	Zhuang et al. (2022); Choi and Suh (2020); Zhang et al. (2025)
New parts with no history	Similarity-based forecasts from part attributes	Initial stock set conservatively and reviewed early	Caserta and D'Angelo (2025)
Parts facing obsolescence	Decay methods that reach zero	Run-down targets; avoid new buys	Prestwich et al. (2021)
Low-volume, critical parts	Forecast by segment, as above	Consider dual sourcing with additive manufacturing	Knofius et al. (2021); Aljuaid et al. (2023)

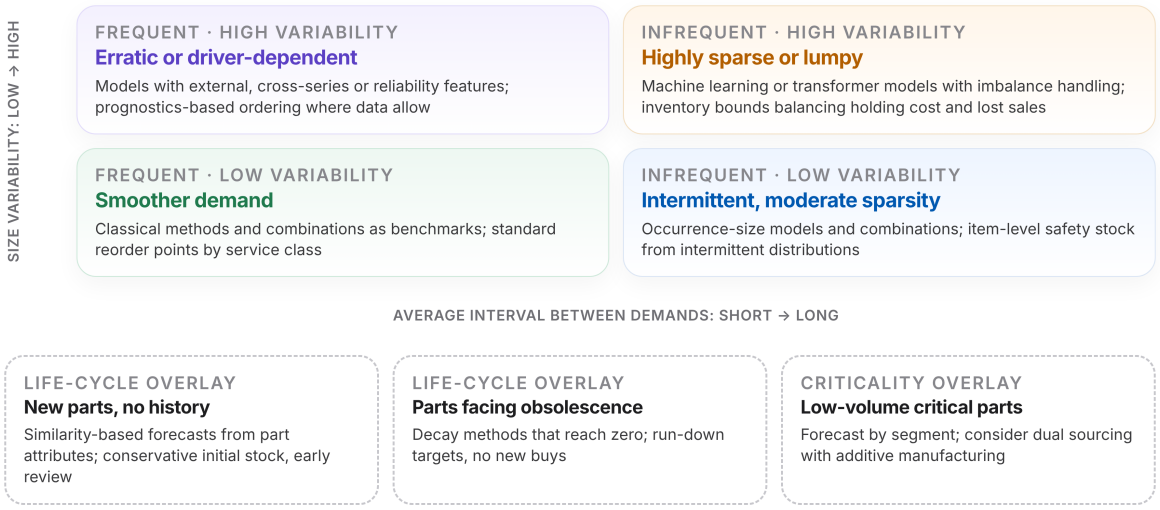

Figure 2. Default mapping of spare parts demand segments to forecasting and inventory approaches in the proposed DSS

Because the framework has not been implemented, its expected value is argued from evidence rather than measured. Each component is traceable to studies reporting benefits in comparable settings: decomposition and combination methods to automotive and production data (Li et al., 2023; Rožanec et al., 2022; Zhuang et al., 2022), item-level optimisation to safety stock reductions at maintained service in the automotive industry (Sfiris & Koulouriotis, 2025), and controlled transition to budget-compliant fill-rate improvement (Haubitz & Thonemann, 2021). We propose that a Saudi pilot evaluate the DSS on a rolling-origin basis against the organisation's current method, using both accuracy measures and inventory measures such as fill rate, stock value, turnover and obsolete stock, and that planner overrides be analysed to identify where human judgement adds or removes value.

In answer to RQ3, the DSS should integrate a broad data foundation, demand profiling and segmentation, a method library with cost-oriented automated selection, inventory optimisation by part class, controlled transition to new policies, and monitoring with planner feedback, and it should be evaluated on inventory outcomes as well as forecast accuracy.

8 Discussion and limitations

The review suggests that the main obstacle to better spare parts management is not the lack of forecasting methods but the lack of systems that match methods to demand segments, connect them to stock decisions and manage implementation. The evidence on machine learning is encouraging but conditional: its advantages appear in sparse or information-rich settings and depend on careful handling of imbalance and missing data. Simpler methods, especially exponential smoothing for demand size, remain competitive and should not be abandoned. A DSS that keeps both, and selects between them on cost-oriented criteria, is more defensible than a wholesale switch to complex models.

For Saudi practitioners, three implications follow. First, data integration should come before advanced modelling; parts histories, vehicle parc and supersession information are prerequisites for useful forecasts. Second, the powertrain transition and model localisation will increase the share of parts with short histories or uncertain futures, so methods for new and obsolescent parts deserve

early attention. Third, given limited adoption of structured improvement methods, implementation should be staged, with training and transparent explanations of recommendations, and with stock changes phased to protect budgets.

For researchers, the gaps are clear. No peer-reviewed study in the corpus evaluated an automotive spare parts forecasting or inventory system using Saudi data. Comparative studies on Saudi dealer and distributor data, research on demand for electric vehicle parts in hot climates, and field studies of how planners interact with DSS recommendations would all add value.

The study has limitations. Only 30 journal articles were reviewed, and several key studies come from aviation, military and heavy-duty vehicle settings rather than passenger car aftermarkets, so transfer to Saudi automotive firms is argued rather than demonstrated. Some evidence was checked against abstracts only. One researcher screened and synthesised the literature. The decision rules in Table 2 are evidence-informed defaults, not optimised parameters, and the framework's value remains to be tested empirically.

9 Conclusion

Spare parts demand in the automotive aftermarket is intermittent, lumpy and increasingly shaped by localisation and electrification. Drawing on 30 recent studies, this paper has shown that good spare parts decisions depend on matching forecasting methods to demand segments, converting forecasts into item-level stock decisions with cost-oriented criteria, handling new and obsolescent parts explicitly, and controlling the transition to new policies. It proposed a six-component DSS for Saudi automotive enterprises that brings these elements together with planner feedback, and an evaluation protocol for testing it. The framework is offered as a basis for implementation and empirical validation in Saudi dealer and distributor networks, where the evidence base is still thin.

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