ZIBELINE INTERNATIONAL™ PUBLISHING

ISSN: 2821-2983 (Online)
CODEN: MBMJAO

Malaysian Business Management Journal (MBMJ)

DOI: http://doi.org/10.26480/mbmj.01.2024.01.05

CrossMark

RESEARCH ARTICLE

INTEGRATING PEST ANALYSIS AND PREDICTIVE MODELLING: AN ANALYSIS OF USED CAR MARKETS AND PRICING IN CHINA

Hongtao Chen[a], Peishi Wu[b*]

[a] UW-Madison, 500 Lincoln Dr 27 Bascom Hall Madison, Wisconsin 53706, United States
[b] Shenzhen Graduate School of Peking University, Shenzhen 518000, China
**Corresponding Author Email: serena.ps.wu@gmail.com*

ARTICLE DETAILS

Article History:

Received 23 September 2023
Revised 26 October 2023
Accepted 01 November 2023
Available online 03 November 2023

ABSTRACT

With the sustained development of China's used car market, an intricate analysis and comprehension of this sector become paramount. This investigation incorporates both PEST (Political, Economic, Social, and Technological) analysis and Gaussian Process Regression (GPR) predictive models to discern the various determinants of the Chinese used car market and to precisely forecast the prices of used vehicles. Initially, the PEST analysis delineates how an amalgamation of macro-environmental factors, including policy shifts, economic trends, societal inclinations, and technological advancements, coalesces to influence and mould the used car landscape. Subsequently, the GPR predictive framework furnishes a data-driven approach to pricing, with the findings highlighting the original new car price, horsepower, and engine displacement as pivotal factors influencing used car valuation. This study proffers invaluable insights for policymakers, used car distributors, and manufacturers, facilitating a refined comprehension of market dynamics and the formulation of efficacious strategies.

KEYWORDS

Chinese used car market, PEST analysis, Gaussian Process Regression (GPR), used car price forecasting, policymakers, used car distributors.

1. Introduction

As the world's premier automotive market, China wields considerable influence over the global automotive industry. While new car sales have garnered substantial scholarly attention, the increasingly vital used car market warrants further exploration (Ellencweig et al., 2019). With consumer sentiment shifting, regulatory frameworks evolving, and innovative financial tools propelling change, the used car market emerges as a significant realm warranting a more profound analysis (Ren, 2022). This article enriches the understanding of China's used car market dynamics by synergising Political, Economic, Social, and Technological (PEST) analysis with predictive modelling.

The PEST analysis facilitates an examination of macro-environmental factors affecting China's used car market. It explores how policy transformations (like regulatory liberalisation), economic trends (such as the emergence of financial instruments), societal shifts (such as the evolution of consumer attitudes), and technological advancements shape this arena (Ellencweig et al., 2019; Fayziyev et al., 2022). In the study's second segment, insights derived from the PEST analysis guide a used car pricing prediction model (Liu et al., 2022). Incorporating these macro-environmental variables into the model engenders a comprehensive, nuanced understanding of the price determinants in China's used car market.

In the present study, the Gaussian Process Regression (GPR) predictive model was employed (Alajmi and Almeshal, 2021; Liu et al., 2022; Sidiropoulos et al., 2021). Initially, input and output variables for the GPR model were ascertained through expert interviews and a comprehensive literature review. Following data pre-processing, the GPR model was constructed. Subsequently, the developed GPR model was utilized to forecast the prices of used cars. Within the predictive pricing model segment, the development and implementation of the mathematical model for used car price prediction augmented valuation accuracy.

This model contemplates various factors, including mileage, vehicle age, condition, and model, to forecast market prices (Liu et al., 2022). Such an approach ensures equitable pricing, obliterates guesswork and proves beneficial to both purchasers and vendors. The emergence of this model introduces heightened consistency and reliability in pricing for the used car market. By amalgamating PEST analysis with the Gaussian Process Regression predictive model, this research furnishes novel theoretical and practical perspectives for pertinent studies, policy formulation, and strategic decision-making in the used car market.

2. Literature Review

An exhaustive review of the literature was undertaken in the exploration of various factors influencing the Chinese second-hand car market. By employing the PEST analysis framework, these factors were categorised into four primary domains: political, economic, social, and technological.

2.1 Political factors

Political factors assume a significant role in shaping the Chinese second-hand car market, encompassing aspects from license plate auctions to environmental policies, and the enforcement of consumer protection regulations (Feng et al., 2012; Liu et al., 2021). The license plate auction system, implemented in several major cities, impacts the accessibility and pricing of used cars. This system indicates that consumers purchasing second-hand vehicles with accompanying license plates can circumvent participation in competitive license plate auctions, consequently enhancing the demand in the second-hand car market and escalating the prices. Concurrently, green license plate policies promote the usage of new energy vehicles, altering the supply-demand relationship of traditional

Quick Response Code	Access this article online	
	Website: www.mbmj.com.my	**DOI:** 10.26480/mbmj.01.2024.01.05

Cite The Article: Hongtao Chen, Peishi Wu (2024). Integrating Pest Analysis and Predictive Modelling: An Analysis of Used Car Markets and Pricing in China. *Malaysian Business Management Journal, 3(1): 01-05.*

second-hand cars.

These policies may augment the supply and diminish the demand for traditional second-hand cars, thereby affecting their pricing. The recently abolished second-hand car migration policy by the Chinese government could increase the circulation of second-hand cars, instigating changes in market dynamics, including supply, demand, and pricing (Wang, 2022). However, it is noteworthy that there exist no national regulations specifically targeting the second-hand car market at present, necessitating consumers to adopt additional preventive measures (Binding, 2014; Li and Zhou, 2012). Thus, it is imperative to remain alert and sensitive to subtle policy changes and regulation adjustments, for a comprehensive understanding and prediction of the future trends in the Chinese second-hand car market.

2.2 Economic Factors

Economic constituents exert profound influences on the Chinese second-hand vehicle market. Predicated on the nation's fiscal health, including consumers' discretionary income, the availability of financial instruments, or the overall volatility of the economic landscape, the used car sector experiences substantial repercussions. Both economic prosperity and recession bear significant implications for the used car market; periods of economic flourish may amplify demand for second-hand vehicles, subsequently driving price escalation, whereas periods of economic stagnation potentially mitigate demand and price (Torok, 2020). The level of consumers' discretionary income directly impacts the demand within the used car market, thus subsequently influencing vehicle pricing (Biswas et al., 2014). Furthermore, the availability of financial instruments exerts a far-reaching effect on the used car sector. Financial instruments can broaden the potential customer base for the used car market, while the terms and conditions of these tools markedly influence consumer decision-making and the dynamics of the used car market (Foohey, 2020).

2.3 Societal factors

Societal variables also play a pivotal role in shaping the second-hand car market. These factors encompass societal acceptance of used vehicles, urban societal structures, and consumer psychology. Attitudes towards second-hand vehicles can directly sway market dynamics. The degree of societal acceptance of used cars directly impacts market demand and pricing (Lin et al., 2021). Moreover, consumer perceptions of automobiles significantly influence the types of used cars in demand within the market and their pricing (Zhao and Zhao, 2020).

2.4 Technological factors

Technological advancements have engendered a profound transformation in the landscape of the second-hand automotive market, inclusive of the emergence of digital platforms and the development of predictive pricing models. These digital platforms for used automobiles have not only simplified the transaction process but also enhanced transparency, fostering consumer confidence, and thereby exerting substantial influence on the second-hand vehicle market (Ellencweig et al., 2019). Databases for vehicle information have contributed significantly to the maturation of the used car market, furnishing reliable data pertaining to vehicle histories, and thereby elevating consumer trust (Chen et al., 2020). Lastly, the impending transition towards Electric Vehicles (EVs) may usher in significant modifications in the supply-demand dynamics and pricing within the used car market (Fayziyev et al., 2022). In summation, technological factors are playing a cardinal role in sculpting the contours of the second-hand automotive market.

A comprehensive analysis across these four domains provides profound insights into the intricacies of the Chinese second-hand car market and guidance on predicting and adapting to market fluctuations. A PEST analysis elucidates how political, economic, social, and technological factors collaboratively shape the Chinese used car market, in comparison with the United States market. Anticipation builds for future research endeavours to delve further into the interaction of these variables and provide sustained insights for the continued evolution of the used car market.

3. Methodology

3.1 Application of Gaussian Process Regression

In the landscape of machine learning techniques, Gaussian Process Regression (GPR), a method grounded in Bayesian theory, undoubtedly captures the attention of academic researchers. As documented by Alajmi and Almeshal, GPR finds extensive application across various domains for regression tasks (Alajmi and Almeshal, 2021). Diverging from traditional parametric regression techniques, GPR employs a non-parametric Bayesian approach, manifesting exemplary performance even with limited training data. A group researchers further underscore that this technique is particularly germane to datasets of small to medium scale, attributing its pronounced advantages in terms of accuracy and simplicity (Sidiropoulos et al., 2021).

A few critical distinctions between Gaussian Process Regression (GPR) and other regression techniques, particularly when juxtaposed with neural networks, merit attention. Parkinson and Wang emphasized that a salient feature of GPR is its capacity to quantify the uncertainty associated with predictions, an attribute of paramount importance in scenarios demanding an assessment of predictive confidence or reliability (Parkinson and Wang, 2023). Moreover, GPR models furnish uncertainty estimates corresponding to each prediction, facilitating the decision-making process and affording a profound comprehension of the model's predictive robustness.

Furthermore, the interpretability intrinsic to GPR models enables researchers and decision-makers to discern the relationships between input and target variables with greater lucidity. Wilson and Nickisch accentuated that, due to the paucity of hyperparameters in GPR, it exhibits computational efficacy when managing smaller datasets and can further mitigate computational expenses via sparse approximations (Wilson and Nickisch, 2015). In contrast, neural networks might encompass an extensive array of parameters, with their interrelations potentially being more intricate and elusive in interpretation. However, the computational complexity of GPR is also one of its constraints, especially when grappling with voluminous datasets.

For the application under study, GPR was chosen to conduct a predictive analysis of the pricing in China's used car market. This selection predominantly emanates from GPR's capacity to quantify predictive uncertainties and its commendable model interpretability. The model's input parameters were discerningly chosen, grounded in a comprehensive understanding of the used car market and meticulous consideration of pivotal factors influencing used car prices. These encompass brand, drivetrain, horsepower, car body type, mileage, date (month), engine displacement, fuel consumption, environmental standards, original new car price, and the history of parts replacement. Such factors elucidate multiple dimensions of used car pricing, with the model's output denoting the transaction price of the used vehicle. To optimize GPR performance, specific kernel functions were chosen, and hyperparameters were rigorously selected and adjusted. Throughout the application, unique dataset characteristics were taken into account, ensuring optimal GPR performance.

Furthermore, data acquisition and processing constituted a quintessential segment of this study. To bolster the analysis's precision and credibility, 946 data sets were amassed from the Aokangda Corporation. To capitalize on this data and ensure the robustness of the model, the data was bifurcated: 70% served as the training set, undergoing 10-fold cross-validation, while the residual 30% acted as the test set, evaluating the model's generalization capabilities on unseen data. Through such partitioning and validation strategies, it endeavoured to guarantee that the GPR model excels not merely on training data but also proffers reliable predictions in practical applications.

3.2 One-hot Encoding

One-hot encoding serves as a strategy to transform categorical variables into binary vectors. This technique establishes a novel feature for each categorical level, subsequently generating a binary attribute for each category (Mansoori et al., 2023). Owing to the incapacity of numerous algorithms to directly process categorical data within the realm of machine learning, one-hot encoding facilitates the conversion of such data into a numerical format, thereby furnishing suitable inputs for various machine learning algorithms (Mansoori et al., 2023).

A salient advantage of one-hot encoding lies in its capacity to preserve the distinctiveness of each category. As elucidated by this encoding mechanism ensures that the post-encoded data aptly represents the original categorical variable, circumventing the introduction of misleading numerical associations (Arat, 2022). Moreover, one-hot encoding addresses the ordinal nature of categorical variables, guaranteeing that the sequence between categories is not misconstrued as a meaningful numerical relationship (Arat, 2022). Concurrently, compared to alternatives such as label encoding or ordinal encoding, one-hot encoding exhibits superior performance when handling categorical variables by eschewing the introduction of data noise or bias (Pargent et al., 2022).

To execute one-hot encoding, it is imperative first to discern categorical variables within the dataset. These variables signify discrete categories or groups, such as brands, drivetrains, or environmental standards. Subsequently, a novel binary feature is crafted for every unique category level of each categorical variable. The dataset, upon utilizing these newly constituted binary features in place of the original categorical variables, will encompass a set of binary features representing diverse categories of the original variables (Cerda and Varoquaux, 2020). However, one-hot encoding is not devoid of challenges, the most salient being dimensionality. This could culminate in an abundance of binary features, thus ushering in a high-dimensional feature space, augmenting computational complexity, and potentially leading to the so-called curse of dimensionality (Cerda and Varoquaux, 2020). To mitigate these issues, dimensionality reduction techniques can be employed to truncate feature volume while retaining pivotal information (Cerda and Varoquaux, 2020).

In this investigation, one-hot encoding was applied to data from the Chinese used car market, especially encoding features like brands, drivetrains, body types, and environmental standards. Following this encoding, the original categorical features have been transmuted into a series of binary features. These features aptly encapsulate the categorical information from the original data, offering a more conducive input for machine learning algorithms while ensuring data integrity and preservation of its innate significance.

3.3 Evaluation and Feature Significance in Gaussian Process Regression

In the assessment and optimization of the Gaussian Process Regression (GPR) model, the utilization of appropriate evaluative metrics and a comprehensive understanding of feature significance remain paramount. The Mean Absolute Error (MAE) serves as a prevalent metric to quantify discrepancies between predicted and actual values, measuring the average magnitude of errors within a set of predictions. The Root Mean Square Error (RMSE) offers insights into the average magnitude of predictive errors, facilitating comparisons in units consistent with the original dataset.

Another pivotal metric, the coefficient of determination R^2, quantifies the extent to which the model elucidates the variance of the target variable, thereby appraising the model's data fit quality (Liu et al., 2022). Regarding the assessment of feature significance, the F-test emerges as an essential statistical approach, determining feature significance through the evaluation of the relationship's prominence between features and the target variable. In essence, for Gaussian Process Regression models, both evaluation and feature selection epitomize the central steps to ascertain model accuracy and performance. Only by selecting apt evaluative metrics and delving into feature significance can researchers comprehensively comprehend model performance, enabling informed decision-making.

4. RESULTS AND ANALYSIS

4.1 Outcomes from the Gaussian Process Regression Model

For the prediction of prices in the Chinese used car market, this study employed the Gaussian Process Regression (GPR) as the primary analytical model. Several pivotal metrics warrant attention during model evaluation, as illustrated in Figure 1. Initially, the Root Mean Square Error (RMSE) merits consideration. With a value of 9.3199 on the validation set, this metric diminishes to 7.523 on the test set, suggesting heightened precision in forecasting for hitherto unencountered test data. Subsequently, the Mean Absolute Error (MAE) reflects a congruent trend: 4.8904 for the validation set and a reduced 4.3067 for the test set, reinforcing the model's proximity to actual values when predicting for the test dataset.

Additionally, the coefficient of determination (R^2) stands at 0.94 for the validation set, escalating to 0.96 for the test set. An R^2 approaching unity indicates the model's adeptness at elucidating a significant proportion of the variance in the target variable, thus signifying its exceptional fitting capability, as depicted in Figure 2. Therefore, predicated upon these evaluative metrics, one might posit that the Gaussian Process Regression Model manifests superior performance in predicting used car prices, especially demonstrating notable accuracy and generalization capabilities with previously unseen data.

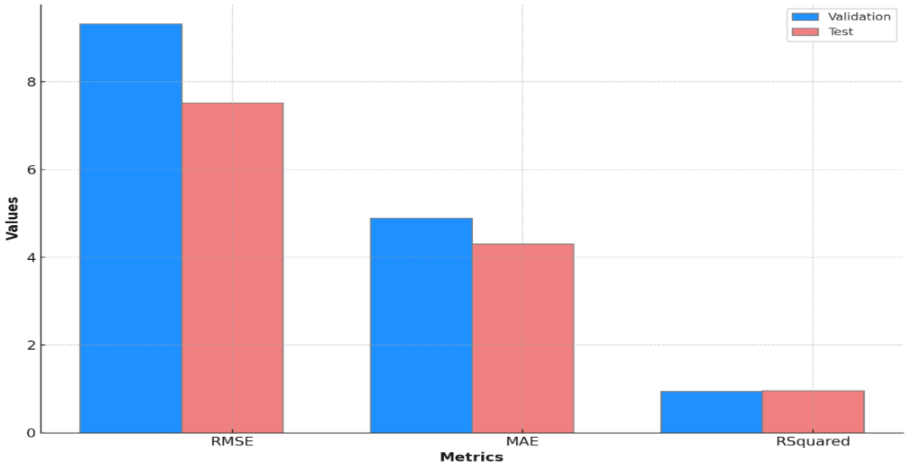

Figure 1: Evaluation Metrics for the Used Car Price Prediction Model

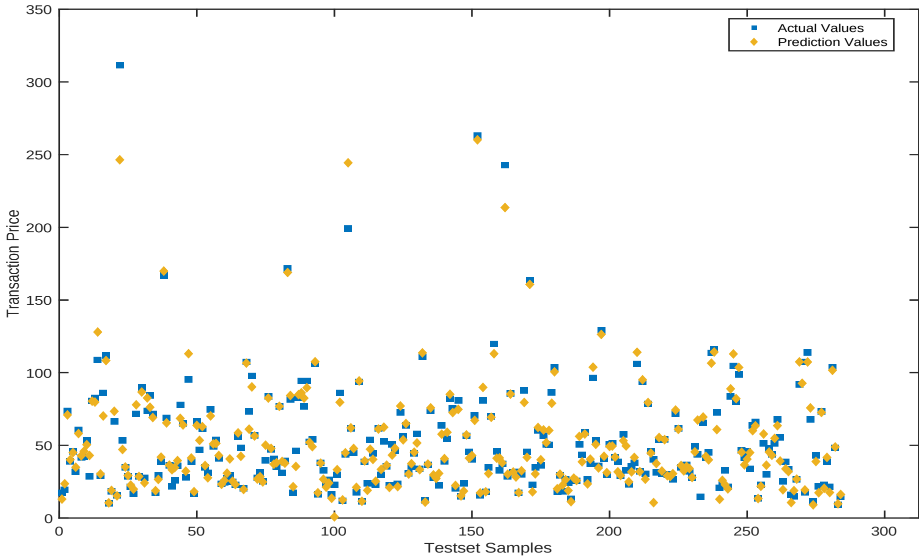

Figure 2: Comparison of Predicted and Actual Values of Used Car Price using the Gaussian Regression Model on an Unidentified Dataset

4.2 Feature Significance

To probe the pivotal determinants influencing the pricing of used vehicles, this study assessed the importance of various characteristics, as illustrated in Figure 3. The assessment elucidated that 'Original New Car Price', with a score of 360.1905, markedly surpasses other attributes, rendering it the paramount factor in predicting the price of used vehicles. This aligns with empirical observations since the initial acquisition cost of a vehicle largely delineates its resale value in the market. 'Horsepower' and 'Displacement' received scores of 179.2085 and 158.0741 respectively, both crucial for price prognosis. Notably, horsepower, representing a quintessential performance metric of a vehicle, correlates closely with its power and driving experience, whereas displacement links with fuel efficiency and vehicle performance, both pivotal metrics considered by consumers during acquisition. Moreover, 'Brand' and 'Fuel Consumption' received scores of 125.2325 and 101.194 respectively, underscoring their significance in the used car market valuation. Brands frequently associate with a vehicle's reputation, quality, and perceived value, while vehicles with lower fuel consumption gain increasing favour with the rise in environmental awareness.

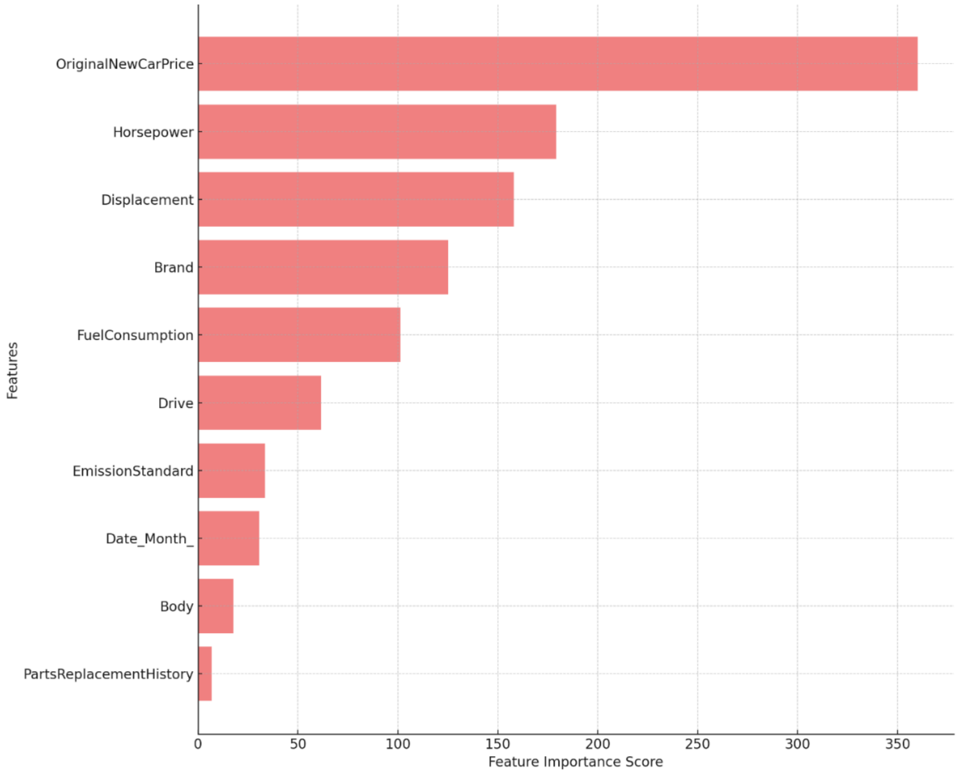

Figure 3: Top 10 Important Features for Used Car Pricing Prediction

Attributes such as "Drive" (drivetrain), "EmissionStandard" (emission standards), "Date_Month_" (purchase date), "Body" (body type), and "PartsReplacementHistory" (history of part replacement) contribute variably to the market value of used cars, scoring 61.5718, 33.5347, 30.6527, 17.7212, and 6.6861, respectively. Notably, with the tightening of environmental regulations, vehicles adhering to stringent emission standards have become increasingly sought after. The purchase date directly corresponds to a vehicle's age, subsequently influencing its market value. Moreover, the vehicle's body type and history of parts replacement might, to a certain extent, determine its desirability and value in the marketplace. The body type influences a vehicle's utility and aesthetic design, thus determining its appeal. A frequent parts replacement history could signify underlying vehicular issues, potentially diminishing its market value. In essence, these data underscore that the original new car price, horsepower, and displacement are the predominant determinants of used car prices, while other factors exert varying degrees of influence on the market value of used vehicles.

4.3 Discussion and Analysis

The performance evaluation of the Gaussian process regression model indicates discernible strengths and limitations. The model exhibits exemplary prowess in forecasting second-hand car prices, particularly with regard to its accuracy and generalization capabilities on unfamiliar data sets. Specifically, its R^2 value approaches 1, implying the model's capacity to account for a substantial proportion of the variance within the target variable, further corroborating its robust fitting competence. Moreover, endowed with Bayesian properties, the Gaussian process regression offers uncertainty estimates for each prediction, bolstering the reliability of the decision-making process. Nonetheless, when juxtaposed with neural networks, the computational intricacy associated with handling extensive data sets remains a salient constraint. While techniques to mitigate computational complexity exist, these methods are not invariably feasible or straightforward.

Integrating the PEST analysis with the Gaussian Process Regression predictive model, this study offers not only profound insights into the Chinese used car market from political, economic, social, and technological dimensions, but also furnishes a data-driven forecasting approach for market pricing. For future research trajectories, there lies potential in amalgamating the PEST analysis with other sophisticated machine or deep learning models to augment predictive accuracy. Additionally, broadening data sources to comprehensively capture the intricacies and dynamic shifts of the market, as well as further refinement of the models, are areas meriting exploration.

In practical application, policymakers ought to remain cognizant of the ramifications political factors bear upon the market, ensuring that relevant policies and regulations harmoniously balance market health and consumer interests. Acknowledging the pivotal role of brands and technology, used car dealers and manufacturers should amplify the quality, technological prowess, and reputation of their vehicles. With the incessant evolution of society and technology, continuous market research emerges as vital to monitor and adapt to these shifts.

In summary, this investigation adeptly melds PEST analysis with the Gaussian Process Regression predictive model, shedding innovative light on research, policymaking, and strategic decision-making for the used car market. Nonetheless, as every study possesses inherent limitations, this research anticipates further validation and refinement to bolster its reliability and precision in practical application.

5. Conclusion

This research innovatively integrates the PEST analytical framework with the Gaussian Process Regression (GPR) predictive model, offering novel insights into the dynamics and pricing strategies of China's used car market. Initially, utilizing the PEST analysis, the study delves into the interplay of political, economic, social, and technological factors that collectively influence and mould the Chinese used car landscape. Subsequently, through the employment of the Gaussian Process Regression predictive model, the study introduces a data-driven methodology for forecasting used car valuations. The results of the model evaluation are notably impressive, particularly when addressing unseen data sets. Further scrutiny identified the initial new car price, horsepower, and engine displacement as paramount influencers on used car valuations.

This investigation not only furnishes fresh theoretical and pragmatic perspectives on the used car market research but also serves as a valuable reference for policy-making and strategic decision-making. Prospective studies might contemplate integrating the PEST analytical framework with other advanced machine learning or deep learning algorithms to further elevate forecasting accuracy. Moreover, expanding data sources is imperative to holistically apprehend market intricacies. In pragmatic application, policymakers used car dealers, and manufacturers stand to gain immensely from this study. Policymakers, to ensure the robust growth of the market and safeguard consumer rights, need to accord substantial emphasis on the ramifications of political elements, ensuring the appropriateness of related policies and regulations. Concurrently, used car dealers and manufacturers ought to incessantly bolster their brand image and technological prowess to meet consumer demands more efficaciously.

REFERENCES

Alajmi, M.S., and Almeshal, A.M., 2021. Modeling of cutting force in the turning of AISI 4340 using Gaussian process regression algorithm. Applied Sciences, 11 (9), Pp. 1-11.

Arat, M.M., 2022. Learning From High-Cardinality Categorical Features in Deep Neural Networks. Journal of Advanced Research in Natural and Applied Sciences, 8 (2), Pp. 222-236.

Binding, J., 2014. Consumer protection law in the People's Republic of China. China-EU Law Journal, 3 (3-4), Pp. 223-252.

Biswas, A., Mukherjee, A., and Roy, M., 2014. Leveraging factors for consumers' car purchase decisions: A study in an emerging economy. Journal of Management Policies and Practices, 2 (2), Pp. 99-111.

Cerda, P., and Varoquaux, G., 2020. Encoding high-cardinality string categorical variables. IEEE Transactions on Knowledge and Data Engineering, 34 (3), Pp. 1164-1176.

Chen, J., Ruan, Y., Guo, L., and Lu, H., 2020. BCVehis: A blockchain-based service prototype of vehicle history tracking for used-car trades in China. IEEE Access, 8, Pp. 214842-214851.

Ellencweig, B., Ezratty, S., Fleming, D., and Miller, I., 2019. Used cars, new platforms: Accelerating sales in a digitally disrupted market. McKinsey & Company.

Fayziyev, P., Ikromov, I., Abduraximov, A., and Dehqonov, Q., 2022. Timeline: History of the electric car, trends and the future developments. Eurasian Research Bulletin, 6, Pp. 89-94.

Feng, S.W., Li, Q., and Xu, D., 2012. The private car license plate auction in Shanghai: macro-effectiveness and micro-mechanisms. In CICTP 2012: Multimodal Transportation Systems—Convenient, Safe, Cost-Effective, Efficient, Pp. 118-129.

Foohey, P., 2020. Consumers' Declining Power in the Fintech Auto Loan Market. Brook. J. Corp. Fin. & Com. L., 15, Pp. 1-44.

Li, S., and Zhou G.Y., 2012. The problems of China's Consumer Protection Law in the legal practice? International Journal of Business and Social Science, 3 (14), Pp. 1-8.

Lin, H., Chen, Z., and Wu, S., 2021. Influencing Factors of Users' Intention to Purchase in the Online Used Car Market in China: Influencing factors in the online used car market. 2021 5th International Conference on Business and Information Management,

Liu, D., Wu, Y., He, Y., Qin, L., and Zheng, B., 2021. Multi-Object Detection of Chinese License Plate in Complex Scenes. Computer Systems Science & Engineering, 36 (1), Pp. 1-12.

Liu, E., Li, J., Zheng, A., Liu, H., and Jiang, T., 2022. Research on the prediction model of the used car price in view of the pso-gra-bp neural network. Sustainability, 14 (15), Pp. 1-19.

Mansoori, A., Zeinalnezhad, M., and Nazarimanesh, L., 2023. Optimization of Tree-Based Machine Learning Models to Predict the Length of Hospital Stay Using Genetic Algorithm. Journal of Healthcare Engineering, Pp. 1-14.

Pargent, F., Pfisterer, F., Thomas, J., and Bischl, B., 2022. Regularized target encoding outperforms traditional methods in supervised machine learning with high cardinality features. Computational Statistics, 37 (5), Pp. 2671-2692.

Parkinson, J., and Wang, W., 2023. Linear-Scaling Kernels for Protein Sequences and Small Molecules Outperform Deep Learning While Providing Uncertainty Quantitation and Improved Interpretability. Journal of Chemical Information and Modeling, 63 (15), Pp. 4589–4601.

Ren, H., 2022. The Current Situation of China's Used Car Market and Development Suggestions. 2022 7th International Conference on Financial Innovation and Economic Development (ICFIED 2022),

Sidiropoulos, E., Vantas, K., Hrissanthou, V., and Papalaskaris, T., 2021. Extending the Applicability of the Meyer–Peter and Müller Bed Load Transport Formula. Water, 13 (20), Pp. 1-18.

Torok, L., 2020. The link between car sales and the economic crisis in the European Union at the time of the Covid-19 epidemic. International Journal of Economics and Business Administration, VIII(4), 1033-1042.

Wang, H., 2022. Research on the Used Car Marketing Strategy After the Breaking of the Relocation Restriction Policy. Academic Journal of Science and Technology, 2 (2), Pp. 112-117.

Wilson, A., and Nickisch, H., 2015. Kernel interpolation for scalable structured Gaussian processes (KISS-GP). International conference on machine learning,

Zhao, Z., and Zhao, J., 2020. Car pride and its behavioral implications: an exploration in Shanghai. Transportation, 47 (2), Pp. 793-810.