PRICE DETERMINATION OF USED VEHICLES IN NEPAL

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By

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DECLARATION

I hereby declare that this thesis entitled "PRICE DETERMINATION OF USED VEHICLES IN NEPAL" which I have submitted to the Department of Economics, Patan Multiple Campus, in partial fulfillment of the requirements for the Degree of MASTER OF ARTS in ECONOMICS, is entirely my original work prepared under the guidance of my supervisor. I have made due acknowledgements to all ideas and information borrowed from different sources in the course of writing this thesis. The results of this thesis have not been presented or submitted anywhere else for the award of any degree. I shall be solely responsible for any evidence found against my declaration.

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Sagar Chapagain

LETTER OF RECOMMENDATION

This thesis entitled "PRICE DETERMINATION OF USED VEHICLES IN NEPAL" has been prepared by Mr. Sagar Chapagain under my guidance and supervision. I, hereby, recommend it in partial fulfillment of the requirements for the Degree of MASTER OF ARTS in ECONOMICS for final examination.

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Date: July 2024

LETTER OF APPROVAL

We certify that this thesis entitled "PRICE DETERMINATION OF USED VEHICLES IN NEPAL" submitted by Sagar Chapagain to the Department of Economics, Faculty of Humanities and Social Sciences, Patan Multiple Campus, Tribhuvan University, in partial fulfillment of the requirements for the Degree of MASTER OF ARTS in ECONOMICS has been found satisfactory in scope and quality. Therefore, we accept this thesis as a part of the said degree.

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ABSTRACT

The used car market has a high perception of lemon within the market because of information asymmetry and lack of transparency between the buyers and sellers. The mistrust and information asymmetry can be resolved by making the market more transparent and making the information available freely among all the stakeholders. The solution is to determine pricing of used cars, i.e. when factors affecting car price are determined, it not only supports in direction to reduce information asymmetry but also gives a ground for used car sellers a space to justify their pricing. This study explores the price dynamics of the used car market, taking into account a range of intrinsic vehicle attributes. This study implemented a hedonic pricing technique in order to evaluate the factors affecting pricing of used cars. This study employed two functional forms of hedonic model i.e. semi-log and box-cox transformation using OLS method. The study found Age and mileage of cars shows a negative correlation with price. In addition to age, few brands, fuel type, and drive are found to be important price-determining elements, although gearbox type and color are not much significant in the given dataset. Interestingly, Car bodies including hatchbacks, SUVs, sedans, and pickups seem to be more expensive indicating that buyers prefer more luxury vehicles. Furthermore, pricing and engine capacity has a positive relation, indicating that consumers prefer to pay more to higher performing cars. This model provides valuable and insightful information that can help customers, dealers, and policy makers to make more informed decisions and strategize in the used automobile market and work together to support growth of industry as a whole.

Keywords: Hedonic Pricing Technique, Price Determination, Lemon perception, etc.

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ACRONYMS AND ABBREVIATION

OECD	Organization for Economic Co-operation and Development
NADA	National Automobile Dealers Association of Nepal
GDP	Gross Domestic Product
PDA	Personal Digital Assistants
CAGR	Compound annual growth rate
CPO	Certified Pre-Owned
OLS	Ordinary Least Square
RMSE	Room Mean Squared Error
CC	Cubic Centimeter
4WD	4 Wheel Drive
2WD	2 Wheel Drive
SD	Standard Deviation
AIC	Akaike information criterion
BIC	Bayes information criterion
VIF	Variance Inflation Factor
FMA	Frequentist Model Averaging
HPM	Hedonic Pricing Model
ADAS	Advanced Driver Assistance Systems
SIAM	Society of Indian Automobile Manufacturers
DoTM	Department of Transport Management

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CHAPTER I
INTRODUCTION

1.1 Background

The term “used car”, also referred to as a pre-owned vehicle, is a motor vehicle that has been previously owned by one or more individuals or entities and is sold through various channels including dealerships, private sales, and auctions. Used cars offer significant cost savings compared to new vehicles, primarily due to the rapid depreciation that new vehicles undergo within the first few years of purchase. This depreciation means that used cars often provide better value for money, with many consumers able to afford higher-end models or brands that would be out of reach otherwise. Used cars are heterogeneous products and durable goods as opposed to fungible goods, each car has their own unique characteristics i.e. age, brand, condition, engine capacity and so on which contributes to its value (McManus & Sweeney, 2018).

The “used car market” is one sector of the automotive industry that is involved in buying and selling used vehicles. The market for used vehicles forms a critical component of the automobile industry, providing an affordable and accessible transportation option for a diverse range of consumers. In Nepal, the used market includes a variety of imported and locally sourced vehicles, providing affordable options for consumers. The used car market is very crucial in management of transportation of Nepal’s transportation system, offering alternatives to the purchasing of new vehicles (Prasain, 2019).

Understanding the dimensions of used vehicles is important for accurate price determination, especially for a diverse market like Nepal. Several key factors collectively define the value of a used vehicle, impacting its market price. Firstly, the age of a vehicle is a significant determinant, as newer vehicles generally command higher prices due to less wear-tear and more advanced features (McManus & Sweeney, 2018). Closely related is the mileage, with lower mileage often indicating less mechanical wear, thus enhancing the vehicle's value (Kahn, 2018). The brand and model also play a pivotal role; reputable brands known for reliability, such as Toyota and Honda, are often priced higher (Baumol & Blinder, 2008). Additionally, the overall condition of the vehicle, encompassing both mechanical state and cosmetic appearance, is critical. Well-maintained vehicles with documented service histories can fetch premium prices, providing buyers assurance about their longevity and performance (Einav & Levin, 2014).

Moreover, engine capacity and body type significantly impact pricing; vehicles with larger engines or advanced hybrid technologies tend to be priced higher due to their enhanced performance and efficiency benefits (Oliver & Berndt, 2019). The presence of desirable features and options, such as advanced infotainment systems, safety features, and luxury add-ons, also adds to a vehicle’s value. The service and maintenance history provide insight into how well the vehicle has been cared for, with comprehensive records often leading to higher prices (Horan et al., 1980). Market dynamics, including demand and supply, significantly affect pricing. For instance, popular models in limited supply can see inflated prices (Lancaster, 1966; Rosen, 1974).

In addition, the number of previous owners and the vehicle's usage history also matter; cars with fewer owners and those used personally rather than commercially are typically valued higher (Doležalová, 2020). Geographical location also plays a vital role, as vehicles in urban areas with higher living costs might be priced more than those in rural settings due to differing market conditions and consumer preferences (Waske & Katare, 2023). Proper documentation and legal compliance ensure that the vehicle is legally sound, impacting its marketability and price positively. Also, technological advancements within the vehicle, such as Advanced Driver Assistance Systems (ADAS) and connectivity features, can significantly enhance its value (Saari et al., 2021).

The dimensions of used vehicles collectively interact with market conditions, influencing the equilibrium price of used vehicles. Comprehensive analysis and understanding of these factors are essential for making informed buying or selling decisions in the Nepalese used car market. This multifaceted approach to price determination acknowledges the heterogeneity of used vehicles, aligning with contemporary economic models that account for product differentiation and consumer preferences (McManus & Sweeney, 2018; Einav & Levin, 2014).

Traditional economic models often assume the product as homogeneity, which is unrealistic for many real-world goods like used cars, which are differentiated by features such as mileage, sun roof, engine type, and manufacture year (Horan et al., 1980). These differences shift the demand curve based on consumer preferences, with desirable features driving demand and prices up, and less desirable features having the opposite effect. The equilibrium price of used cars emerges from the interplay of supply and demand through buyer-seller negotiations (Einav & Levin, 2014). Recognizing the complexity of pricing heterogeneous goods, Lancaster (1966) and Rosen (1974) introduced the Hedonic Pricing Model (HPM), which assesses how specific attributes contribute to a product's overall price. Unlike Comparable Market Analysis (CMA), which compares similar vehicles, and Depreciation Models, which calculate value loss over time, the HPM provides a detailed valuation by isolating the impact of individual characteristics. This makes the HPM particularly effective in capturing the unique aspects of each vehicle, offering a more precise valuation in markets with high product heterogeneity (McManus & Sweeney, 2018).

Automobiles play a significant role in human lives since they have long served as a means of transportation for people. The quantity and variety of cars being created are rapidly rising along with the human population (N.C. Government & Heritage Library, 2020). The Hedges Company (2023) estimates that there are approximately 1.474 billion vehicles on the planet in 2023. Many presume that North America might be the region where automobiles are most prevalent. However, Asia accounts for more than one third of all automobiles, while Europe in second. It is estimated that alone in the continent of Asia, there are approximately 518 million automobiles in total. As it is evident that as the Economy of countries increases , there will be increase in number of ownership of private vehicles as with increase in Per Capita Income of people , people are more interested to grow their living standard hence, this number will undoubtedly continue to increase given the current circumstances (OECD projects global growth to be 2.7% in 2023, i.e., people's economic strength is continuing to rise).

Automobiles were once regarded as a luxury in Nepal, but that is no longer the case since motorbikes are now seen as a need rather than a luxury, and even cars are now accepted as the norm (Neupane, 2018). This is supported by the increase in quality of ongoing road constructions and poor quality of mass transportation within the country. With increase in purchasing capacity of people with migration to foreign land, this trend is rapidly growing and is common among the young aged population.

The market for used automobiles worldwide was estimated to be worth $1.4 trillion in 2021, and it is anticipated to increase to $2.6 trillion by 2031, rising at a CAGR of 6.5% between 2022 and 2031. In the meantime, the Asia Pacific region expects to grow the used car market by the fastest in the world with a CAGR growth of almost 7.7% during the forecasted period, majorly because of rapid growth in income, high demand for cars in Asia and increase in classified cars platform and dealership certified pre-owned (CPO) program (Waske & Katare, 2023).

In the United States, the used car market is larger than the new car market, with over 40 million used vehicles sold annually. The US used car market is characterized by a high level of transparency, with numerous resources available for consumers to verify vehicle histories, compare prices, and obtain financing (Spyne, n.d.). Similarly, Japan, known for its strict vehicle inspection regulations and high standards of vehicle maintenance, is a major exporter of used cars. Japanese used cars are highly demanding in many developing countries due to their reliability and good conditions. The country's robust auction system and the availability of detailed vehicle history reports and pricing prediction models contribute to the transparency and efficiency of the market (Sako & Helper, 1998). The European used car market is also significant, with a strong focus on certified pre-owned programs and stringent emissions standards. The European market is influenced by factors such as environmental regulations, economic conditions, and consumer preferences for specific brands and models (Saari et al., 2021).

The used car market trends that are becoming increasingly popular in the automotive industry includes increasing investment by operating players. Leading companies in the used automobile market are focusing on increasing investments for business expansion and bolstering their competitive position. Certified pre-owned programs offered by manufacturers ensure that used cars meet specific standards of quality and reliability, providing additional peace of mind for buyers (OICA, 2022).

The used car market in South Asia, comprising countries such as India, Pakistan, Bangladesh, and Sri Lanka is characterized by rapid growth and significant potential. Economic development, increasing urbanization, and a growing middle class have fueled the demand for used vehicles across the region. India, the largest market in the region, has seen substantial growth in the used car segment. According to the Society of Indian Automobile Manufacturers (SIAM), the used car market in India is projected to grow at a compound annual growth rate (CAGR) of 11% from 2021 to 2026. Volkswagen, a premium car manufacturer, is planning to digitally connect used vehicle dealerships in major developing countries. For this it aims to open 21 of used vehicle shops in India, which allows it to focus more intently on financial investments in the used car market. Hence growth of the used automobile industry can be seen (Mukherjee, 2024). The proliferation of online marketplaces, increasing consumer awareness, and the availability of financing options have contributed to this growth (SIAM, 2023). However, the market remains fragmented and faces several challenges, including regulatory hurdles, market transparency and access to financing.

The total number of motor vehicles operating in Nepal reached more than 3.1 million as per the report released by Department of Transport Management (DOTM) in April 2017/18 also the report highlights that only 88,735 motor vehicles were registered in FY 2006/07, the number climbed to 444,259 units in FY 2016/17 i.e. the registration has increased fivefold during the last decade which shows how the demand of automobiles is increasing in Nepal. According to Nepal Automobile Dealers Association (NADA), the automobiles sector is contributing Rs 100 billion worth of taxes to the treasury every year although the contribution of the used car industry on taxation is not yet known. Hence, the automobile market is contributing to the quality of life of people as well as contributing towards economic growth of the country (Poudel, 2018).

In Nepal, with an increase in purchasing capacity of people with migration to foreign land, this trend is likely to grow rapidly and might be common among the young population (Uprety, 2017). The used car market is going to boom in developing countries like Nepal. Although income of people in Nepal is increasing but due to the government's high taxation policy on first hand car price considering it as a luxury good, increase in cost of living i.e. high rate of inflation in Nepal, as well as the frequent import ban for luxury goods (including automobiles), the Nepalese automotive sector always prefers second hand vehicles and it can be easily expected that the market of Nepalese second hand automotive business is yet to grow more in coming future (Karki, 2022).

Although there lies tremendous opportunity in Nepal for the used vehicles market, there are some transparency problems associated with the used car market. It is not only the problem of Nepal but related to the overall used car industry all over the world. Akerlof (1970) in his study found that the used car market is not efficient, as there exists asymmetric information between buyers and sellers. This is because the sellers of cars are more informed about the qualities and features associated with the vehicle while the buyer is less informed. Hence there exists a gap in the information as a result of which the social welfare obtained is lower than that would have been in case of information symmetry.

There are majorly three problems associated with the growth of used car markets:

1. Unorganized Dealers and mistrust for consumers
2. Lack of Transparency in the Unorganized Sector
3. Price Manipulation by Dealers

Unorganized Dealers and mistrust for consumers: Although the used cars market is expected to witness remarkable growth in the future, owing to the high cost associated with new cars, the used car market industry is highly unorganized and dominated by few car dealers which will limit the market growth and does not support the market for perfect competition and hence the overall social welfare is reduced. A research on consumers by Lades (2017) found that the automotive market is among the top three least trusted markets in Germany. Similarly, Ghita et al. (2023) concluded that there exists adverse selection in used car markets from a comparative analysis of Second hand cars prices in Romania and Germany. Since there always exists information asymmetry among the buyer and seller. One research by Ghita et al. (2023) found that there exists the perception of Lemon among consumers which will restrict the used car market to be transparent and there always remains the mistrust among buyer and seller. The dealers or sellers try to manipulate or influence the information of quality of a car to the consumers and try to restrict fair competition. The major problem for the used car to maintain a fair competition and is mistrust among consumers in the used car market is driven by the lack of transparency and potential price manipulation in both the unorganized sector and within some organized dealer operations.

Lack of Transparency in the Unorganized Sector: The unorganized segment of the used car market often involves individual sellers or small-scale dealers who operate with varying degrees of transparency. Consumers might be uncertain about the true condition of the vehicles, their history, and fair pricing. This lack of clear information can lead to mistrust as buyers may fear hidden defects, undisclosed accident histories, or inaccurate mileage readings which is supported by the research by Ghita et al. (2023) hence there always exists a perception of Lemons. Although new car sellers are dominated by small quantity of sellers and there's no very less possibility to distort the information so New car pricing is a transparent mechanism, but in case of used cars since there are variety of vendors and there is more space to distort the information leading to information asymmetry (Waldman, 2003). Without proper standardized processes, warranties, or reliable inspection procedures, consumers may find it challenging to make informed decisions, thereby increasing their skepticism about the offerings in the unorganized market. Baumann et al. (2021) found that easing data access to consumers, increasing the efficiency of sales related processes and by expanding the competences of the sellers or dealers can help to improve the current market situation.

Price Manipulation by Dealers: On the other hand, some established dealers within the used car market can contribute to consumer mistrust by engaging in price manipulation tactics. This involves inflating the prices of vehicles beyond their actual value, either through misleading advertising or persuasive sales tactics. Such behavior can lead to buyers feeling taken advantage of, eroding trust in the industry. Additionally, dealers might offer seemingly attractive deals but include hidden fees, warranties, or add-ons that substantially increase the final cost. Consumers who discover these tactics after a purchase can feel deceived and, consequently, be wary of future interactions with dealers. This will eventually impact the overall trust of consumers and decrease the overall social welfare of the society. A similar research of Volkswagen's 2015 emission scandal in Israel by Ater et al. (2018) has shown that the sales of cars with manipulation fell by 18% and resale of these Volkswagen cars fell by 6%. Hence it can be seen that manipulation and tactics can impact the overall industry. In contrast to developed economies, the Nepalese used car market suffers from information inefficiency and does not contain sufficient price information of used cars for consumers. The National Automobile Dealer Association (NADA) in the USA, may be given as an example, which provides a guidebook about the prices of all types of used cars to domestic consumers.

Unlike developed economies, the Nepalese used car market is plagued by information inefficiency and lacks adequate price information for consumers. In contrast, the National Automobile Dealers Association (NADA) in the USA provides a comprehensive guidebook on the prices of various used cars for domestic buyers (Erdem & Şentürk, 2009). Price determination of used vehicles helps consumers to take a wise decision thereby reducing information asymmetry. Hence, this study aims to identify the key factors influencing used vehicle pricing to predict future prices based on vehicle features. By doing so, it aims to reduce price manipulation and inflating prices, fostering a layer of trust between dealers and consumers. This trust can help both parties share benefits more equitably, ultimately contributing positively to the economy.

1.2 Statement of the problem

The high demand for used cars provides an affordable alternative for many consumers in Nepal (Poudel, 2018). However, the used car market faces significant challenges related to pricing transparency, information asymmetry, and market inefficiencies, creating uncertainty and diminishing consumer confidence (Ghita et al., 2023). These issues ultimately hinder the market's overall efficiency.

In Nepal, consumers often struggle to determine the true value of used vehicles due to the absence of standardized pricing processes, unreliable inspection procedures, and potential price manipulation by some sellers (Baumann et al., 2021). This vulnerability is exacerbated by a general mistrust of used car dealerships, fueled by concerns over misleading advertising and aggressive sales tactics (Lades, 2017). These dynamics compromise transaction transparency and fairness and impede the market's overall functioning. Studies has shown that when buyers and sellers possess unequal information about a vehicle's history and condition, it creates mistrust and uncertainty, further reducing market efficiency (Akerlof, 1970). Addressing these issues is critical to optimizing the market, ensuring fair pricing, and enhancing overall market efficiency. Finding a solution that can estimate a price that is acceptable for both buyer and seller can end the mistrust among the potential stakeholders.

Hence, a potential solution lies in developing a robust mathematical model for used car price determination in Nepal. By incorporating various car characteristics such as age, features, brand, mileage, and condition, such a model can provide a more objective and data-driven approach to valuation (Baumann et al., 2021). This approach can empower consumers to make informed purchasing decisions and deter price manipulation by sellers, fostering a more fair and competitive market environment (Ghita et al., 2023). This study aims to address the lack of transparency and information asymmetry in Nepal's used car market by leveraging a mathematical model for price determination. By doing so, it seeks to empower consumers, promote trust within the market, and contribute to a more efficient and equitable used car market in Nepal (Sharma, 2019). The research question for the study are:

- What are the key factors influencing the pricing of used vehicles in Nepal?
- How do the descriptive statistics and distribution patterns of the variables in the dataset provide insights into the underlying data trends and relationships?

1.3 Objectives of the study

The main objective of this study is to understand overall factors that affect pricing of used vehicles based on consumer behavior and preferences of features. Hence, the specific objectives for the study are as follows:

- To analyze the factors affecting the used car pricing
- To analyze the descriptive statistics and distribution patterns of the variables in the dataset.

1.4 Significance of the study

The significance of this study on investigating the main determinants of used vehicle pricing in Nepal is rooted in addressing critical gaps and challenges within the automotive market. Nepal's reliance on imported vehicles combined with high government taxes on new automobiles creates a significant barrier to car ownership for many individuals, leading to a high demand for affordable options in the used car sector. However, this demand is hindered by issues related to pricing transparency, information asymmetry, and market inefficiencies. This study is essential because it aims to empower prospective car buyers with valuable insights into how specific attributes influence used car prices. By identifying and analyzing key determinants such as vehicle age, features, brand reputation, mileage, and condition, the study can provide consumers with informed decision-making tools. This knowledge enables consumers to make choices aligned with their preferences and budget constraints, fostering a more equitable and consumer-friendly marketplace.

Moreover, the study's contribution extends beyond consumer empowerment to improving market transparency and efficiency. The findings from this study hold significant implications for policymakers and industry stakeholders. Evidence-based insights into the determinants of used car pricing can inform policy reforms related to import taxes, regulations, or incentives within the automotive sector. Policymakers can leverage these insights to design interventions that enhance market accessibility, affordability, and overall economic efficiency. For instance, understanding how specific attributes influence vehicle prices can guide tax policies that make car ownership more attainable for a broader segment of the population. Moreover, by promoting fair pricing practices and increasing market transparency, the study's findings can foster a more equitable and consumer-friendly marketplace, benefiting both consumers and dealers by fostering trust and credibility.

In addition to its practical applications, this study contributes valuable knowledge to the academic understanding of consumer behavior, market dynamics, and pricing mechanisms within the unique context of Nepal. By identifying and analyzing key determinants such as vehicle age, features, brand reputation, mileage, and condition, the study contributes valuable knowledge to the academic understanding of consumer behavior, market dynamics, and pricing mechanisms within the unique context of Nepal. Overall, the significance of this study lies in its potential to drive positive change, empower stakeholders, and contribute to the advancement of both academic and practical understanding in the realm of used vehicle pricing and market dynamics.

1.5 Scopes & Limitations

1. The reliance on data from classified ads platforms like hamrobazar.com and nepalicars.com may introduce biases, as these platforms and the datasets may not fully represent the entire used car market in Nepal.
2. The study focuses on observable attributes (e.g., age, mileage, brand etc.) to predict used car prices, neglecting important unobservable factors such as vehicle maintenance history, seller reputation, or sometimes critical attributes like accident history and actual vehicle condition, economic variables are missed, which could influence pricing dynamics.
3. The hedonic pricing technique assumes linear relationships and independence of variables, which may oversimplify the complex interactions between attributes and price outcomes in the used car market.

1.6 Outline of the Study

This study is organized into several sections to facilitate a comprehensive exploration of the determinants of used vehicle pricing in Nepal and their implications. The structure of the study is outlined as follows:

Chapter 1: Introduction

This chapter contains the general background and introduction of this study. The chapter consists of subtopics including overview and background of study, the research problem, objectives, significance of study and limitations of study, which is followed by the chapter Literature review.

Chapter 2: Literature Review

The Literature review chapter reviews previous studies and literature that are related to this study subject and also looks for the research gap within earlier literatures to add new research gaps to the stack of knowledge. This topic covers various recent studies done internationally and nationally for the given topic of study.

Chapter 3: Research Methodology

The third chapter is Research Methodology, which discusses the research methodology of this study including research design, data collection methods, variable selection criteria and statistical techniques employed in the analysis.

Chapter 4: Data Presentation and Analysis

Research Methodology is followed by Data Presentation and Analysis, in the fourth chapter which discusses the nature of data collected, descriptive analysis of raw data, its characteristics with the help of graphs, tables and more importantly results of the empirical analysis (statistical analysis), including regression outputs, insights into the determinants of used car prices, and model performance evaluation also interprets the findings in light of theoretical perspectives and compares them with existing literature based on objectives of the study.

Chapter 5: Summary and Conclusion

The fifth chapter is Summary and Conclusion which concludes the study by summarizing key findings, contributions to the field, and avenues for future research and policy implications.

CHAPTER II
REVIEW OF LITERATURE

2.1 Introduction

This study is about price determination of used cars in Nepal, which can contribute to the used car industry as a whole by providing a scientific and statistical way to determine a price of car such that minimizing the information asymmetry, and price manipulation by dealers such that the buyer and society can increase overall social welfare, supporting with a ground for a healthy trust among car buyers and dealers and minimizing the possibility of price manipulation and information asymmetry. Such that the overall industry can have a perfect competition and reduced information biases so the overall used car industry has a fertile ground for growth.

The literature review aims to provide an overview of existing research on the price determination of used cars. It explores previous studies, methodologies and findings related to the price determination methods and also finding research gaps.

The purpose of this section is to provide a comprehensive understanding of the existing study on price determination of used cars. It further explores the international context of study carried out to understand how pricing of used cars are defined and implemented worldwide to give a base and fundamental understanding in the implementation of pricing of used cars. Similarly, the study further focuses and reviews studies that have been conducted in the context of Nepal in used cars pricing dimension. Finally, going through these articles the study can find out the research gap and shortcomings and pave the way for further study to contribute to better understanding of used cars pricing in Nepal.

2.2 Literature Review

2.2.1 International context

Hakim et al. (2024) in his study investigated to find key factors influencing the decision to purchase used cars by using a survey and questionnaire among individuals aged 18-40, interested in purchasing used cars in Jakarta, Indonesia. Further Data analysis revealed the key factors influencing the decision to purchase used cars. The result displayed various factors influence the pricing decisions out of which stands economic considerations such as affordable prices and lower depreciation values compared to new cars, and other personal interest factors like model, brand, fuel efficiency and condition of car had major contributions in buying a car while information factors like well documented service history, dealers assistance and transparency to customer i.e. consumer satisfaction also played a vital role. The issue with this method is that it depends on subjective judgments and experience to determine the pricing of used cars which makes it difficult to assert the same approach in order to estimate pricing of other cars.

Ghita et al. (2023) made a comparative study in the used car industry in the Romanian and German market to check and compare the Lemon perception in the industry by comparing the pricing between those two markets. “Lemon” perceptions refer to beliefs about the existence of low-quality second-hand cars in the market. Such beliefs, as part of a wider socio-economic phenomenon named adverse selection, manifest themselves through risk-aversion attitudes, for instance, a decreased willingness to pay high prices for any used car, regardless of its actual quality. The study used 30,264 data from Romanian used car ads scraped from Autovit.ro and 1,308,575 car ads extracted from Mobile.de for Germany. The study utilized statistical tests such as the Shapiro-Wilk test and the paired Wilcoxon test to confirm its findings. Although the study found out that both of the market has a certain degree of information asymmetry and mistrust among the car buyers. Interesting insight this study revealed was that the lemon effect is found to be higher regardless of whether the price of the car is high or low, even though the pricing of similar used cars in Romania is higher than that of Germany, the adverse selection phenomenon in the German market is more visible than that of Romania. Additionally, this study also found that the public in Romania are found to be less concerned about the information asymmetry in relation to the German market. Hence, this study concludes that the lemon phenomenon is prevalent in used car markets regardless of the cost and place, which ultimately creates a mistrust between buyer and seller and there exists a certain level of information asymmetry which hinders the growth of overall industry ultimately reducing the utility to consumers as well as the overall industry.

Alhakamy et al. (2023) examined the impact of various features on the prices of used cars and to develop empirical solutions for estimating these prices by employing various regression and machine learning models. The study on the pricing of used vehicles highlights the significant impact of various economic and social factors on car ownership and market dynamics. Numerous studies underscore the necessity of owning a car for daily commuting and essential activities, emphasizing the financial burden of purchasing new vehicles amid economic challenges. Consequently, there has been a notable shift towards the used car market, where affordability becomes a pivotal concern. Methodologically, this study has employed machine learning and big data analytics to model and predict used car prices, with linear regression. Findings from the study indicates that specific features, such as car age, mileage, and brand, significantly influence price estimation. Conclusions generally affirm the efficacy of linear regression models in predicting used car prices, supporting the market's sustainability by providing more accurate pricing information to consumers. However, the implications for sustainability extend beyond mere pricing, as accurate price predictions can facilitate better market transparency and consumer decision-making, potentially leading to reduced economic waste and more efficient resource use. Despite these advancements, a notable research gap exists in the context of regional markets, such as Nepal, where localized economic conditions and market characteristics may affect price determination. Addressing this gap, the present study aims to explore the determinants of used vehicle prices in Nepal, leveraging hedonic regression model to provide region-specific insights and enhance market sustainability.

Kumar (2023) conducted a study examining markets characterized by asymmetric information about used car prices and aimed to predict these prices using advanced machine learning techniques. The initial dataset required extensive cleaning to handle outliers and missing data, ensuring it was suitable for analysis. Through exploratory data analysis, the study identified key features that significantly impact car prices. Four machine learning algorithms—Linear Regression, Random Forest, Extra Tree Regressor, and Extreme Gradient Boosting Regression—were employed to develop predictive models. Among these, the Extra Tree Regressor demonstrated superior performance, achieving a prediction accuracy of approximately 95%. The findings underscore the efficacy of machine learning models, particularly tree-based algorithms, in accurately predicting used car prices by incorporating multiple influential factors. The study also culminated in the development of a cloud-based application that provides car price estimations, offering valuable guidance to users. However, Kumar's study identifies a critical gap: the need for localized studies to tailor these predictive models to the specific market conditions in Nepal, thereby enhancing the accuracy and reliability of used car price determinations in the Nepalese context.

Huang et al. (2023) investigated the economic rationale behind certified pre-owned (CPO) programs, examining how they add value for both durable goods firms and consumers by enhancing market efficiency. The study, relevant both academically and practically, delves into the adverse selection literature and the "lemons problem," highlighting the role of CPO programs in mitigating market inefficiencies. Using a game-theoretic model tailored to durable goods, the research explores how the specific features of CPO programs, such as program size and qualification criteria, contribute to market efficiency. Data and empirical analysis from the U.S. automotive industry were employed to validate the theoretical findings. The results revealed that CPO programs enhance market efficiency through two main mechanisms: effective segmentation of buyers into high- and low-quality product categories and increased trade-in discounts for used product owners. These mechanisms not only boost revenue but also encourage the trade-in of high-quality products, leading to more new product purchases and increased secondary market sales. The study concludes that larger CPO programs further strengthen these effects, thereby improving overall market efficiency. Managerial implications suggest that firms can enhance their CPO programs by strategically setting trade-in discounts and managing price discrimination between CPO and non-CPO products. The literature review underscores the study's contribution to understanding the practical impacts of CPO programs and their role in addressing information asymmetries in the market. Future research could explore additional factors influencing the effectiveness of CPO programs across different market conditions, further enriching the understanding of their economic impact.

Baltas and Giakoumaki (2023) examined the factors influencing the values of classic car models and explain the significant price differences among them, addressing a notable gap in the existing literature. Their study developed and tested a set of research hypotheses regarding the effects of model characteristics on market values using a generalized hedonic price model that also considered brand heterogeneity. The data were derived from various classic car models, focusing on attributes such as aesthetics, rarity, engineering, and performance. The findings revealed that the value of classic car models is determined by observable characteristics, and brand identity significantly impacts model values even after accounting for these attributes. The study concluded that measurable factors like aesthetics and rarity are crucial in determining classic car values. This research provides empirical evidence on value formation in the classic car market, emphasizing the unique role of brands. The implications suggest that both collectors and investors should consider these observable factors and brand identities when evaluating classic car models. The literature review highlights the originality of the study, as it is one of the first to empirically examine classic car model value formation, offering new insights into an intriguing yet understudied market. Future research could expand on these findings by exploring other dimensions of value formation in classic cars and similar collectible markets.

Pillai (2022) investigated to develop an intelligent framework for estimating the cost of used cars using artificial Neural Network algorithms and he compared it with regression models, simple machine learning models and neural network models. Some other studies imposed various machine learning models and neural networks to evaluate the pricing of the used cars, while others used simple regression models and others tried to compare both machine learning, neural networks and Regression models. The total dataset included in the study by Pilai was 175,000 used car data, with 35,000 were test data while 140,000 datasets were a set of training data which was taken from the US market for 30 popular US car brands. According to the study, Artificial neural networks outbid all the other models, out of which Artificial Neural Networks are built with the Keras regression algorithm, and its performance was compared with the basic models such as linear regression, decision tree algorithms, gradient boosting, and random forests. The Neural Network model resulted with a mean absolute percentage error of 11% and R^2 value explained 96% of variations which outperformed all of the other models. Although other studies also showed that Neural networks have better performance for huge datasets but for smaller datasets the performance for neural networks or a regression model is identical or sometimes the neural network cannot effectively predict for a low sample of data. Since the study tends to work for a dataset of 2045, a regression model can be a simpler choice.

Brekke and Al-Yassin (2022) investigated the implications of prospect theory in used car pricing and tried to replicate the findings of Prieto et al. (2014) using a hedonic pricing model. In contrast to the earlier findings, that a causal relationship could be established between pricing and used car characteristics, this study could not assert the relationship. They found that using market-level data does not support the assertion that buyers employ prospect theoretic behavior; it is because of the complexity of car purchasing decisions, which involve numerous factors beyond those tested in controlled laboratory settings. The study also shows that different transmission types (automatic vs. manual) and car age impact price depreciation differently, with automatic cars and older cars showing distinct depreciation patterns. Contrary to prior findings, no significant price drop was observed after the 100,000 km threshold. The authors suggest that using transactional prices instead of ask prices in future studies could improve the precision of hedonic parameter estimations. Overall, the study concludes that the study was inadequate for establishing a causal link between mileage reference points and prospect theory effects in the used car market.

In their comprehensive study, Baumann et al. (2021), investigated whether the integration of recent tools, technologies and reliable car data can mitigate the existing mistrust and uncertainties in the used car market by acknowledging the information asymmetry in the used car market. This study is one of few papers that analyzed whether dealers can get direct benefit and opportunity to reinvent themselves by implementing used car data transparently, implementing emerging tools and technologies to improve their business growth. They used interview methods and analyzed the data from the interview to get the results. Baumann et al.'s study results are promising in case that using technologies and unbiased data and adding advanced data analytics by themselves gives them an opportunity to improve their shortcomings and quality of their service offering. In addition to that, making tools, technologies and data available transparently to the public can significantly improve the accuracy and reliability of car valuations. Their findings suggest that when buyers have access to comprehensive and verifiable car data, their confidence in the market increases, thereby reducing the impact of the lemon phenomenon. Furthermore, the author suggests that, not all car dealers have equal access to the data, hence the price determination of used cars using unbiased data, supported by dealer associations or government initiatives, can significantly enhance market transparency and reduce information asymmetry to be beneficial to all consumers, dealers and industry as a whole. This study finds the research gap that using various tools and methods likewise, the studies associated can contribute to the existing stack of knowledge and can be an addition to the literatures and opens up space for market improvement.

The study by Koç and Kostak (2021) examined the significant price volatility in the used car market in Turkey before and during covid pandemic. They focused only on two top popular car models and brands of Turkey (Renault Megane and Volkswagen Passat). Using the Hedonic pricing model, the study assesses the impact of various factors such as equipment, year, mileage, transmission, fuel type, color, and seller location on car prices in two independent time periods (2020 and 2021). Unlike previous studies which often emphasized pricing of used cars only, this study delves into price fluctuation during the Covid-19 pandemic, offering insights into how external economic shocks and inflation impact car prices. The most significant part of the analysis is that the prices of 2020 model cars are higher in 2021 (even though they were one year old in March 2021) compared to May 2020. Additionally, other findings include the price increases with higher equipment levels, diesel engines, and automatic transmission preferences, while it decreases with higher mileage. The color variables and the variables representing the seller's location are less effective in explaining price variations. This study provides contradictory results to earlier studies as most of the earlier findings showed that seller's location shows significant impact on pricing.

Doležalová (2020) investigated to determine the key technical and additional attributes that influence the market price of used cars in Germany using Hedonic pricing model. In this study, he uniquely found out methodological problem in most of the earlier studies with a large number of variables using a single model that they are not able to deal with the uncertainty arising from the large number of possible determinants of used cars. Hence, Doležalová tried to implement a huge dataset with 470,000 used cars from Germany and other European countries with 57 vehicle characteristics, and in order to improve the uncertainty arising from a large number of variables, implemented a new approach in hedonic model called Frequentist Model Averaging (FMA). The FMA model uses a weighted average of several models' predictions. This can improve predictive performance and robustness. Beside implementing a new methodological approach in used car pricing, the author also extended the literature to test the effect of a geographical division on pricing, along with other factors like status of previous owners and smoke pollution of a car which was itself a new research gap. The study concluded that the taste of color of a car can vary geographically which was also evident by several earlier studies. This study further revealed that the brands were valued based on their country of origin, the authors assumes that it might be because of different technology levels of the country. The study also found that the effect of power of an engine and difference between diesel-powered and petrol-powered vehicles notably varies across four countries i.e. France, Germany, Italy, and Netherlands and the study adds that the status of a previous owner seems to have an important role in the price of a vehicle.

Bauer et al. (2020) assessed whether trusted car data, facilitated by blockchain, could increase market transparency and value for market participants. The study tried to understand the impact of blockchain technology on the used-car market, particularly focusing on the issue of information asymmetries that create uncertainty and distrust between buyers and sellers. The methodology involved a market game with 50 participants, complemented by interviews to gather insights on perceived customer value. Data were sourced from these games and interviews, providing a comprehensive view of the market dynamics. The findings revealed that blockchain technology significantly enhances transparency in the market for used cars, leading to increased sales prices and equitable revenue distribution between buyers and sellers. The study concluded that blockchain creates substantial value for both parties by providing verified and trustworthy car histories. This has important implications for the automotive industry, suggesting that the adoption of blockchain can mitigate the "lemons problem" and improve market efficiency. The literature review emphasizes the study's contribution to understanding how technology can address information asymmetries in markets characterized by distrust. Future research could explore the effects of adoption of technology like blockchain or similar that could support market transparency, on market behavior and investigate other sectors where similar issues exist, thereby broadening the scope of these findings.

A study by Celik and Osmanoglu (2019) studied to predict accurately the second-hand car prices for effective market transactions. This study aims to establish a linear regression model to predict the prices of second-hand cars by identifying and analyzing key variables. They tried to establish which variables are significant and which of them are insignificant. Among 78 factors affecting car prices, 23 significant variables were selected based on data from 5041 second-hand cars, achieving a determination rate (R2) of 89.1%. The model was then used to predict car prices through a machine learning algorithm, utilizing training and test data splits of 70-30% and 80-20%. The results revealed a high correlation between actual and estimated prices, with a predictive accuracy rate of 81.15% within a 10% proximity range of true values. This indicates the model's effectiveness in estimating second-hand car prices, although the accuracy could improve with a larger dataset and additional variables. Consequently, the study underscores the potential of machine learning techniques in the second-hand car market while highlighting the need for further research to enhance predictive accuracy. Although the study utilized a machine learning algorithm, the study points out that with the larger dataset, the result by machine learning techniques increases considerably.

A Study by Kihm and Vance (2016) estimated the determinants of prices in both the primary and secondary car markets in Germany, with a specific focus on identifying vehicle attributes that are responsible for retaining the car's value in the used car market. They made comparative measurements and analysis between first and second hand cars. They used a very huge range of dataset containing 371082 observations on new and used cars of 2008 from the car market of Germany. This study uses a hedonic model to find out the influence of technical features and brand name. The study found out that for used cars body type and brand/model name is the highest important feature for retaining its price. Likewise, this study tried to compare the magnitude of pricing across two markets i.e. new and used cars. This study used log transforms also called semi log models for smoothing of the price factors and to reduce the fluctuations. They used various attributes of cars like Age, Mileage, Speed, Engine, capacity, Horse Power, Fuel Consumption, Brand/ Model. It also found out one interesting observation that used cars are on average 7.3% cheaper than new cars when all of the attributes remain almost the same. It revealed a new finding that "the impact of technical features on the car price do not vary substantially between the primary and secondary car markets". This study was insightful in terms that use of various functional forms i.e. log models helps to smooth the pricing of datasets where by reducing the fluctuations.

Prieto et al. (2015) studied the impact of various variables and impact of reliability of used cars in pricing. The study used 1735 French cars to investigate four car models using the hedonic models for determining pricing of used cars. The study used data of car attributes as an independent variable: age, mileage, engine power, engine type (diesel or gasoline), car segment, color, and any extras, including metallic paint, ABS, cruise control, air condition, and navigation. They also included the sellers' type (professional vs private) as a proxy for warranties. Furthermore, The round kilometers (round kms) and the duration of the time the ad was posted (time post) are used as instrumental variables for the seller type variable because round of kms is generally used by private seller than a professional, as well as the professional seller tend to sell their car more quicker than a private seller. They used asking price instead of selling because they found that the asking and selling price are closely correlated even though they are not identical. The study found interesting insights that the mean pricing of a car sold by a professional is 12% higher and diesel engines are 17.5% more expensive. Prieto et al. also gave some strategic marketing recommendations, since mileage is associated with reliability of a car and also highly negative with the price of a car. For a car with high mileage, sellers can advertise and focus on attributes like engine power, navigation systems or color in marketing efforts to counterbalance the low car value and attract potential consumers.

Erdem and Şentürk (2009) investigated the used car pricing in Turkey in order to find, to what extent the pricing of a car reflects its characteristics. They utilized Hedonic pricing techniques to find the impact of various characteristics in the pricing of used cars. Their study utilized 1074 used cars data from various locations in Turkey. The analysis included car attributes such as make year, mileage (later removed due to high correlation with make year), brand (replaced with "country of origin" as a proxy variable), fuel type, transmission type, color, location, presence of a sunroof, and number of services. They implemented three functional forms of the hedonic model: semi-logarithmic regression, log-linear regression, and Box-Cox transformation regression. Their analysis revealed that production year was the most significant factor influencing price. Additionally, cars from certain countries of origin (e.g., US, Korea, Germany, Japan) commanded higher prices. Specific colors (black and gray), diesel engines, automatic transmissions, sunroofs, and a higher number of services were associated with increased prices. The study also highlights the importance of selecting appropriate functional forms. The study notes that log, semi-log, and log-log transformations facilitate economic interpretation, while the Box-Cox model offers robustness to non-normality but might be sensitive to heteroscedasticity (unequal variance).

2.2.2 National context

The pricing of used cars in context to Nepal or South Asia region is a very new topic of study and specially the mathematical modeling of used car pricing in Nepal is not widely available. However, little study has been done on the purchase decision of cars in Nepal.

The study by Neupane and Shakya (2024) examined the determinants influencing the adoption of two-wheeler electric vehicles (2WEVs) in Nepal during 2022/23, emphasizing the importance of understanding these factors for effective policymaking and strategic planning by manufacturers and distributors. Data were gathered from 387 respondents via an online questionnaire, focusing on variables such as financial incentives, social reinforcement, environmental concerns, charging infrastructure, and price. The analysis employed Exploratory Factor Analysis, correlation, and multiple regression techniques to elucidate the impact of these factors. The results indicated that price, financial incentives, and charging infrastructure significantly influence the adoption of 2WEVs, while environmental concerns and social reinforcement do not show a notable effect. These findings suggest that competitive pricing, financial incentives like tax breaks and subsidies, and an improved charging infrastructure are essential for increasing 2WEV adoption in Nepal. Despite the lack of significant concern for environmental issues among Nepalese consumers, raising environmental awareness through educational campaigns is recommended. The study reveals a research gap in understanding the limited influence of social reinforcement and environmental concerns on EV adoption, suggesting a need for further investigation into these aspects.

The study by Timilsina and Jnawali (2024) investigated Generation Z students' preferences for purchasing two-wheelers in Butwal sub-metropolitan, examining the factors influencing their decisions. Utilizing a primary sample of 395 structured questionnaires collected from youths aged 18-25, the study employs descriptive statistics and chi-square tests via IBM SPSS 25 to analyze the empirical relationships between demographic variables and purchase decisions. Key findings highlight that marital status, occupation, religion, mode of payment, purpose of purchase, family size, and annual income significantly influence two-wheeler brand choices. The study concludes that factors such as manufacturer credibility, reliability, vehicle price, brand image, mileage, maintenance cost, resale value, and facilities play vital roles in purchasing decisions. While focusing on two-wheelers, this study provides valuable insights for determining the price of used cars in Nepal. The identified influential factors, particularly reliability, price, brand image, and resale value, are directly applicable to used car pricing strategies. However, the study's limitations include its specific focus on two-wheelers and a particular demographic, suggesting a need for broader study encompassing diverse vehicle types and consumer groups to generalize findings for the used car market.

Rai and Bhattarai (2024) studied the factors influencing the brand preference in buying passenger cars in Nepal, which focuses on understanding the various factors that influence consumers' brand preference when purchasing passenger cars in Nepal. This review investigates the impact of several independent variables: product attributes, price, appearance, brand personality, and self-congruity. Previous studies present mixed results on the influence of these factors. This study used a six-point Likert scale structured questionnaire used for collection of the primary data from 411 passenger car users. The review highlights that brand personality and self-congruity are more influential in shaping brand preference among Nepalese consumers. Brand personality, which encompasses the human characteristics associated with a brand, significantly impacts consumers' emotional connection to the brand. Self-congruity, the match between consumers' self-concept and the brand image, also plays a crucial role in determining brand preference. These findings suggest that emotional factors outweigh rational factors like price and product attributes when it comes to high-involvement products such as passenger cars in Nepal, which can be a unique insightful and interesting study in case of Nepal’s study on brand preference in buying passenger cars. While this study uses a qualitative method of analysis, this study does not provide numerical information on the strength of impact.

The study by Neupane and Sawagvudcharee (2019) focused on to identify the most significant factors among product knowledge, perceived quality, perceived value, and perceived risk. This study aims to find the factors influencing the purchase intentions of two-wheeler consumers in Nepal during 2017/18. Utilizing a descriptive and causal-comparative research design, data was collected through online and physical questionnaires from 426 respondents in the Kathmandu valley. The methodology involved correlation and multiple regression analysis. Findings indicated that perceived quality and perceived value significantly and positively impact purchase intentions, whereas product knowledge and perceived risk showed no significant relationship. The conclusion emphasizes the importance of enhancing perceived quality and value to boost sales. However, the study's scope was limited to Kathmandu and it was a subjective study, the study did not find any causal relationship with various attributes to be integrated to other similar cars for prediction of used vehicles in Nepal.

Sapkota (2017) studied the purchasing behavior of car consumers in Nepal through a quantitative approach that included discussions, surveys, and the use of both primary and secondary data sources. The study revealed that Nepalese consumers' pricing decisions are primarily influenced by economic factors and price, with only a small proportion prioritizing comfort and style. While consumers exhibit basic familiarity with car makes and models, their purchasing decisions are largely driven by budget constraints and brand recognition. Key findings indicate that mileage, brand, and model are the most valued factors for car buyers in Nepal. Additionally, the study identified significant correlations between previous car ownership and brand familiarity, as well as between family involvement and gender. Pre-purchase information seeking, utilizing various channels such as the internet and advertisements, was also highlighted as a critical aspect of the decision-making process. Overall, the study emphasizes the complexity of consumer behavior in Nepal, underscoring the necessity for marketers to develop tailored approaches to effectively reach and persuade car buyers in this market.

Malla (2016) investigated the factors that lead to brand preference for scooters and determined which significantly influence consumer purchase decisions. Using a quantitative approach, a survey was conducted among 200 scooter users in Kathmandu Valley to gather data on various factors such as comfort, mileage, design, price, color variety, size of the fuel tank, spare parts supply, resale value, and durability. The correlation test was applied to analyze the relationship between these factors and customer satisfaction. The findings revealed that comfort, mileage, and design are the top three factors influencing brand preference, while color variety, resale value, and size of the fuel tank are the least influential. Price, mileage, comfort level, color variety, design, size of the fuel tank, and spare parts supply play a significant role in brand preference, whereas resale value and durability do not significantly impact brand preference among women consumers. The study concludes that scooter brands should focus on enhancing comfort and mileage, as these are critical factors for consumers in Kathmandu Valley. Although resale value and durability are less influential, they should not be neglected. Additionally, ensuring a reliable supply of spare parts is important for maintaining customer satisfaction. One gap in the study is the focus on women consumers, suggesting the need for future study to include a more diverse sample and use qualitative methods for deeper insights.

2.3 Identification of Research Gap

Determining the pricing of used vehicles is a complex process, although such a study could contribute to understanding of purchasing behavior of consumers in Nepal. Yet, there are very few studies that have been carried out to find the factors that affect pricing in Nepal. Very few studies like one by Rai and Bhattarai (2024) tried to understand the car purchasing decisions in case of Nepalese consumers. The study found out that brand image, other features of cars seem to contribute to purchase decisions of people but this did not provide any quantitative information of how much impact it makes on the price in order to predict the pricing of cars.

Similarly, a study by Prado (2009), on three different markets of used cars, found that factors of pricing of cars differ slightly by country and region because the company's position (brand position) in each market differs by country. Hence used car markets have their own characteristics by regional variations. In addition to it, multiple studies like by Auf et al. (2018), Mirzaei et al. (2011), Cheng (2015) also found out there are social and cultural impacts on purchase decisions of used cars. In addition to that various studies have shown that the color choices are based on country and region specific. Colors are more associated with the society and region (Erdem & Şentürk, 2009)

Though few studies have been done in Nepal, regarding brand and color preference on choice of cars and bikes which are basically a qualitative study, few studies like one by

Sapkota (2017), but very little study has been done on used car pricing especially in the context of South Asia and also to be precise in the case of Nepal. This study can fill the research gap of regional variation of used car pricing. So, this study can add to the existing stack of knowledge. Hence, this study on used car pricing in the context of Nepal can provide additional insight on the pricing behavior in the used car domain in Nepal, which can be helpful to predict or estimate the price of used car in Nepal in future which can be valuable to the growth of market as it has potential to reduce the information asymmetry existing in the used car industry and can certainly assist government to make new policies.

CHAPTER III
RESEARCH METHODOLOGY

3.1 Introduction

The research methodology chapter lays the foundation of study on the determinants of used car pricing, employing quantitative techniques. This approach enables us to examine in detail the intricate relationships between different characteristics of vehicles and their impact on prices. This study seeks to provide valuable insights into factors influencing the valuation of used cars by using data from online markets and implementing sophisticated price models. This study helps to provide valuable insights into factors influencing the valuation of used cars by using data from online markets and implementing sophisticated price models. This topic includes various chapters that are required to understand overall methodology of the study. The chapter will cover theoretical and conceptual framework where we can discuss about the foundational theory associated with the study. This topic will be followed by other underlaying methodology of research like research design, nature and source of data, data collection tools, tools of analysis and finally the model specification.

3.2 Theoretical /Conceptual Framework

In order to understand the pricing dynamics of used cars, it is necessary to understand in detail the economics of demand and supply in used cars. Used cars are heterogeneously differentiated durable goods with various features and characteristics affecting their value.

The demand for specific features, such as higher fuel efficiency or a sunroof, can shift the demand curve for used cars. Consumers are willing to pay more for cars with desirable features (demand curve shifts right), while less desirable features may reduce demand (demand curve shifts left). Similarly, the availability of cars with specific features can influence the supply curve. For example, if a particular model year is known for reliability, a higher supply of those cars could shift the supply curve to the right, potentially lowering prices. The equilibrium price of used cars is determined by balancing supply and demand dynamics through negotiation between buyers and sellers (Einav & Levin, 2014).

The pricing of used cars is governed by the demand-supply dynamics. The demand supply of used cars is affected by various intrinsic and extrinsic factors. The vehicle attributes and core features of cars are considered to be intrinsic factors while extrinsic factors include seasonality, economic factors and sellers' motivation and so on. Chen and Hua (2018) focused their study towards consumer preferences, economic conditions, and financing options i.e. extrinsic factors to affect demand while Smith and Brown (2017) highlighted the importance of intrinsic factors like vehicle features such as advanced safety systems and entertainment options, in influencing prices.
This study considers only the intrinsic features of available car variables that includes Brand, Age, Fuel type, Transmission type, Color, Gearbox, Body type, Engine capacity, Mileage of car to determine pricing of used car.

Hedonic Pricing Method:
Determining the pricing of a used car being a heterogeneous differentiated good and a luxury good is not merely possible by assuming it as the traditional economics principles. Hence, Lancaster (1966) and Rosen (1974) developed a different pricing strategy to consider in case of such goods. Which states that a good does not provide any utility by itself instead, it consists of characteristics that hold constituted utility. The market price consumer pays for a given good is related to the utility of these characteristics. Therefore, by comparing the prices of goods with different levels of utility for the characteristic of interest, it becomes possible to quantify their value (Lancaster, 1966).

Hedonic pricing estimation is a technique used in economics to analyze how different attributes or characteristics of a product or service contribute to its overall price. This approach is particularly useful when studying markets where products or services have multiple features that can vary in quality or quantity.
Generally, the Hedonic pricing technique is seen to be more successful in evaluating the weightage of various features/characteristics based on the utility consumer gain. The hedonic model is being used in lots of areas like real state pricing, new car pricing, consumer goods and many more.

If each product has a quoted price p and associated with a fixed value of vector z so that products price is given by

$$p(z) = p\,(z_1, z_2, z_3 .., z_n)$$

The basic hedonic pricing equation is typically expressed as:

$$P_i = \mathcal{F}(X_{i1}, X_{i2}, \ldots, X_{in}) + \in$$

Where:

P_i is the price of i-th good

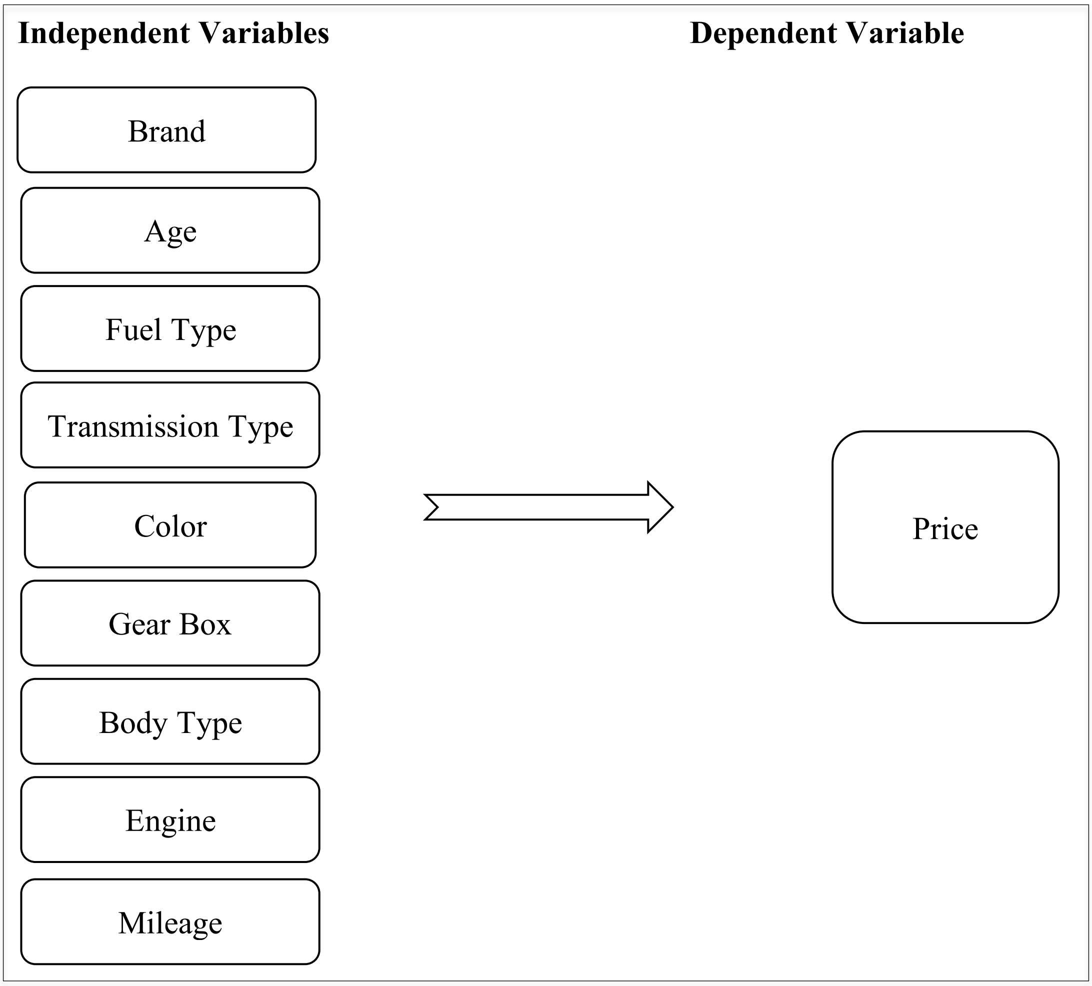
$X_{i1}, X_{i2}, \ldots, X_{in}$ are the n characteristics of i-th good

$\mathcal{F}$ is a functional form (often linear or log-linear)

$\in$ is an error term capturing unobserved factors

Source: (Rosen ,1974)

Figure 1
Conceptual Framework of the study



Source: (Kihm & Vance, 2016; Erdem & Şentürk, 2009)

3.3 Research Design

This study employs the basis of correlational as well as explanatory research design. The correlational aspect involves identifying and measuring the relationships between different car attributes and their prices, while the explanatory component aims to explain these relationships and their impact on pricing. The main objective of this study is to analyze the various intrinsic factors that affect pricing of used cars. The study seeks to understand the factors influencing used car prices and how each attribute contributes to the overall price. This study uses Quantitative research technique i.e. Regression analysis for the analysis of the data. This knowledge can help in reducing information asymmetry in the used car market in Nepal.

To analyze the study, the data is scraped from various Nepal's used cars classified ads platform, the raw data was cleaned and transformed such that data is fit for running various analyses. Finally, an OLS model was used to find the relationship between various variables which is then analyzed. Variables such as Mileage, Age, Brand, Fuel type, Gearbox, Wheel drive, Body type, Color, Engine capacity are used as independent variables while price of car being the dependent variable. Various functional forms of regression models i.e. semi log and Box-Cox transformation will be employed in this study.

3.4 Nature and Sources of Data

The data utilized in this study on the price determination of used cars in Nepal is quantitative in nature, consisting of numerical and categorical information about various car attributes, essential for statistical analyses and regression modeling. The data is collected from secondary sources, specifically from two prominent online marketplaces in Nepal: hamrobazar.com and nepalicars.com, which are widely used for buying and selling used cars. The data are mostly added by the end seller and sometimes by car dealers or professional as well. These platforms provide a rich source of information, including detailed car specifications, prices, and seller details. The data includes listings from the years 2022 and 2023, ensuring relevance and timeliness.

3.5 Data Collection Method

3.5.1 Study Area

The study area for this study is Nepal, focusing on the price determination of used vehicles. The data was scraped from Nepal's renowned classified ads platform, which included comprehensive data on used cars from various cities across Nepal, including Kathmandu, Pokhara, Biratnagar, Butwal, and others. The selection of Nepal as the study area is driven by several key considerations. Firstly, Nepal has a growing market for used cars, fueled by high import taxes on new vehicles and an increasing middle-class population seeking affordable transportation options. This diverse market exhibits distinct demand and supply dynamics influenced by urbanization, economic activities, and transportation needs. By including major cities like Kathmandu, Pokhara, Biratnagar, and Butwal, the study captures a wide range of economic and demographic conditions, offering a comprehensive view of the used car market. Data sourced from a well-established classified ads platform ensures reliability and comprehensiveness, as this platform is widely used across Nepal, providing a robust sample of market transactions.

3.5.2 Sampling design:

The population for this study comprises all used cars listed on online marketplaces in Nepal. The data includes data scraped from renowned classified ads platforms such as hamrobazar.com and nepalicars.com. The study utilizes the overall population available in these websites. The total of 3400 dataset were extracted from those websites, during the cleanup process of the datasets so as to maintain consistency of data, the final dataset was finalized to 2045 after cleanup process.

3.5.3 Data Collection Tools

The data is used in this analysis in secondary data. The study collected data from two of Nepal's renowned classified ads platforms i.e. hamrobazar.com and nepalicars.com. This study used Python programming Language as the tool for regression analysis as well as for data scraping. At first, using python and Selenium (which is a method to run automation scripts in web browsers), the study implemented web scraping scripts with Selenium to fetch all data related to used cars from above mentioned sources. The script basically scraped data such as Brand, Model, Description, Seller name, URL, Phone, Engine size, Mileage, Drive wheel, Fuel type, Gearbox type, Transmission type, Date of ad, Body type posted from those websites.

To ensure the accuracy and reliability of the extracted data, several quality control measures were implemented during the web scraping process. This included validating the extracted data against the original listings on the websites to identify and correct any discrepancies or errors. Additionally, regular monitoring and maintenance of the web scraping scripts were conducted to adapt to any changes in the website's layout or structure. Out of 3400 data sets that were scraped was finally cleaned down to 2045 datasets after the cleaning process.

Cleanup process basically involved two different strategies. The first one being that any dataset entries with missing values in critical variables were dropped. This step ensured that all entries used in the analysis were complete and contained no missing information in these essential fields. The second cleanup process was that the dummy variables (Brand, Color, Body Type) with a unique value count fewer than 50 were dropped to streamline the dataset and reduce complexity. This step focused on retaining meaningful variables while discarding those with limited variation, which would not contribute significantly to analysis and might even introduce noise.

3.6 Tools of analysis:

Multiple linear regression analysis and more specifically Hedonic Pricing model, is used to estimate the coefficients of the empirical model. This technique allows us to assess the relationship between the dependent variable (Price) and Independent variables while controlling other factors. Ordinary least squares (OLS) estimation is used to obtain the best-fitting line through the observed data points and estimate the parameters of the model.

3.6.1 Hedonic Pricing Model

According to Rosen (1974), if there is a commodity with n attributes or characteristics, where $z= (z_1, z_2, \ldots z_n)$. The elements of Z are quantifiable in a way that all consumers' perceptions or evaluations of the quantity of characteristics present in each item are the same.

If each product has a quoted price p and associated with a fixed value of vector z so that products price is given by

The basic hedonic pricing equation is typically expressed as:

$$P_i = \mathcal{F}(X_{i1}, X_{i2},\ldots,X_{in}) + \in$$

Where:

P_i is the price of i-th good

$X_{i1}, X_{i2}, \ldots, X_{in}$ are the n characteristics of i-th good

$\mathcal{F}$ is a functional form (often linear or log-linear)

$\in$ is an error term capturing unobserved factors

3.7 Model Specification

As explained earlier, the model used in this study is Hedonic Pricing model, which explains that the price of a product is determined by the utility of underlying characteristics of the product rather than the utility of the whole product (Rosen, 1974). Hence the model for this study is focused on to predict the price of a vehicle (dependent variable) based on various attributes such as Mileage, Fuel type of vehicle, Gearbox, Color, Body type, Age of vehicle and so on i.e. independent variables.

The study shall use dummy variables to represent the categorical variables such as Brand, Color, Body and so on without falling into the dummy variable trap.

$$Price = \beta_0 + \beta_1 Mileage + \beta_2 Fuel + \beta_3 Gearbox + \beta_4 Drive + \beta_5 Age + \sum_{i=1}^{N} \beta_i * Brand_i + \sum_{j=1}^{M} \beta_j * Body_j + \sum_{k=1}^{O} \beta_k * Color_k + \sum_{l=1}^{P} \beta_l * Engine_l + \varepsilon$$

Source: (Kihm & Vance, 2016; Erdem & Şentürk, 2009)

This equation is the final equivalent function for a hedonic price regression. The functional form for the above model can slightly vary based on the choices and nature of data.

Following functional form of hedonic model are used in this study:

3.7.1 Semi-log Transformation (Log-linear):

In this model, the dependent variable (e.g., price) is transformed using the natural logarithm, while the independent variables (e.g. car characteristics) remain unchanged. To reduce heteroskedasticity among the data Shi et al. (2020) and Griliches (1961) employed Semi Log transformation in price (dependent variable) to transform data in their models. The semi log model in itself explains that the coefficient from the result represents the percentage change in the dependent variable for a one-unit change in the independent variable, assuming all other variables in the model remain constant.

$Ln(Y)=\beta_0+\beta_1X_1+\beta_2X_2\ldots+\beta_nX_n$

3.7.2 Box Cox Transformation:

The Box-Cox transformation estimates the optimal power transformation to make the relationship between the dependent and independent variables as close to linear as possible. Box cox transformation can handle various types of skewed data and stabilize variance and it can be used as a remedy to remove heteroskedasticity, making it useful for improving model fit and meeting normality assumptions (Nwakuya & Nwabueze, 2018). While the problem with Box cox transformation is its complexity in interpretation as interpreting results in the original scale of the data requires back-transformation.

Shi et al. (2020) in their study on used car prices in China, applied the Box-Cox transformation to price as well as numerous attribute data (mileage, age, etc.). They discovered that the selected changes greatly enhanced model fit and produced more precise estimates of how various factors affected price. The same case was seen with the Croes and Vandecappelle (2016) who compared various data transformation techniques like log or Box-Cox who also found that box-cox transformation performed well.

For the Model

$Y=\beta_0+\beta_1X_1+\beta_2X_2\ldots+\beta_nX_n$

The transformation for dependent variable is:

$$Y(\lambda) = \begin{cases} \dfrac{Y^{\lambda} - 1}{\lambda}, & \lambda \neq 0 \\ \ln(Y), & \lambda = 0 \end{cases}$$

3.7.3 Test of Multicollinearity:

VIF (Variance Inflation Factor: It is a measure in regression analysis to quantify the extent of multicollinearity among predictor variables in a statistical model. Multicollinearity occurs when two or more predictor variables in a regression model are highly correlated with each other, which can lead to problems such as inflated standard errors, unstable parameter estimates, and difficulty in interpreting the individual effects of predictors.

$$\mathrm{VIF}(X_i) = \frac{1}{1-R2}$$

Interpretation of VIF:

- A VIF of 1 indicates no multicollinearity, i.e. the predictor variable is not correlated with other variables in the model.
- A VIF greater than 1 suggests that multicollinearity may be present, with values above 5 or 10 often considered slightly concerning, depending on the context.
- VIF values higher than 10 indicate severe multicollinearity, potentially requiring remedial action such as removing highly correlated variables or using regularization techniques.

3.8 Operational Definition of Variables:

Various studies have shown that various features like mileage, age, safety features like airbags, multimedia, model of vehicle, place of sales, availability of workshops and ease of maintenance, economic conditions etc. impact the pricing of used vehicles. Although various literatures have shown that a lot of variables might impact the pricing of used cars but because of limitations on availability of data in Nepal this study has considered a few variables that will be used in the analysis. The variables used here are picked up from various popular classified ads platforms in Nepal, which can indicate that these variables are the most important factors that contribute to the pricing and the basis for making car buying decisions. The dependent variable of the study is the price which is defined in NPR and is a numeric variable. Similarly, the independent variables consist of few numeric variables while the majority of variables are categorical variables.

Table 1
Description of Variables used in model

Variables	Description	Reference Category
Price	Price of Vehicle in Npr. (numeric) (Prieto et al., 2015).	-
Mileage	Speedometer reading in Kilometer (numeric) (Prieto et al., 2015).	-
Age	Approximate age of vehicle in years (numeric) (Prieto et al., 2015).	-
Fuel	Binary Categorical Variable where '1' represents Petrol, 0 represents Diesel) (Erdem & Şentürk, 2009)	Diesel
Gearbox	Binary Categorical Variable (1 for 'Manual Transmission', 0 otherwise) (Erdem & Şentürk, 2009)	Automatic Transmission
Drive	Binary Categorical Variable (0 for '2 Wheel Drive' (2WD), 1 for 4WD (Wheel Drive))	2 WD
$Brand_i$	Dummy Categorical Variable representing different Brands of vehicle (Kihm & Vance,2016)	Renault
$Body_j$	Dummy Categorical variable representing different body types of vehicles (Kihm & Vance,2016)	Van
$Color_k$	Dummy Categorical variable representing different colors of vehicles (Erdem & Şentürk, 2009)	White
$Engine_L$	Dummy variable representing different engine displacement ranges - 0 - 1000 - 1001 - 1500 - 1501 - 2000 - 2001 - 2500 - 2501 - 3000 - 3001 - *This engine range was categorized and justified based on the tax category of Government of Nepal	0-1000 cc

Variables	Description	Reference Category
β_0	Intercept term	-
ε	ε is the error term capturing unobserved factors	-

The price of vehicle used in this study is the asking price of seller, which is not exactly the sold price but this study used asking-price because asking and selling price are closely correlated even though they are not identical (Prieto et al., 2015). Similarly, age variable is calculated by subtracting the manufacturing year with the ads posted year. The Mileage variable is the total km traveled by the car which is same as the speedometer reading of the vehicle. Engine capacity though it's a numerical identity but it was converted into a range. The range is defined as per the taxation rate defined by Nepal Government (Bikemandu, 2023). Similarly, brand name, color, body type, Engine range being categorical variable was transformed to dummy variables. Likewise, few variables that were binary i.e. fuel type, transmission, gearbox.

CHAPTER IV
DATA PRESENTATION AND ANALYSIS

4.1 Introduction

This section covers various features and characteristics of the dataset and analyzes the data. The main objective of this chapter is to present the result of the study which includes the result of Hedonic model that is used in this study. Moreover, this study presents the secondary objective of the study i.e. descriptive statistics as well as statistical analysis of data. Additionally, the topic presents table, graph along with, this study makes comparison and discussions of the results obtained in this study to compare with other related studies and results. This topic also uncovers patterns, trends, and correlations and the features of variables on the factors influencing market valuation. Additionally, this chapter also tries to explain the relationships between car attributes, such as age, mileage, engine type, and body style, and their respective prices.

4.2 Overview of the Study

The study covers the various distribution of used cars in Nepal. This section presents and analyzes the data collected for the study on the price determination of used cars in Nepal.

4.2.1 Global trends and patterns in Automobile

The global automotive industry is projected to grow at a compound annual growth rate (CAGR) of 6.77% from 2023 to 2033, expanding from USD 3,498.4 billion in 2022 to USD 6,861.45 billion by 2033 (Spherical Insights, 2023). This growth is driven by increasing vehicle demand in emerging markets, substantial investments in automotive innovation, and the rise of new business models such as shared mobility and subscription services. Additionally, China and the U.S. remain dominant markets, with China's automotive market growing at a CAGR of 7.3% and the U.S. market showing strong recovery trends. These developments highlight a pivotal era for the automotive sector, marked by both significant challenges and unprecedented opportunities. The China is a clear winner in terms of highest automobile sales, where US stands at second, China sold 28.68 million new vehicles, while US sold 15million units in the same period (Plunkett Research, 2024).

The global automobile industry is experiencing transformative trends that are impacting the pricing of used cars. The demand for EV sales is expected to reach 31.1 million units by 2031 (Plunkett Research, 2024), because governments worldwide advocate for greener alternatives to combat climate change. Rising fuel prices are prompting consumers to prefer fuel-efficient and hybrid vehicles, increasing their demand and consequently their prices in the used car market. Additionally, the ongoing semiconductor chip shortage has severely disrupted new car production, leading to lower inventories and higher prices for new vehicles, which in turn boosts the demand and prices for used cars (Kuhnert et al., 2018). Shared mobility services such as Uber and Ola are altering global car ownership patterns by decreasing the need for personal vehicle ownership. These trends highlight the intricate interplay of global automotive shifts on local used car markets, underscoring the need for adaptive pricing strategies.

4.2.2 International trends and patterns in used car industry

The global used car market is undergoing significant transformations due to economic conditions, technological advancements, and changing consumer preferences. The demand for affordable vehicles is increasing, driven by economic uncertainties and the high cost of new cars, particularly in developing regions (Spyne, 2024). The market for used automobiles worldwide was valued at $1.4 trillion in 2021 and is projected to reach $2.6 trillion by 2031, growing at a compound annual growth rate (CAGR) of 6.5% from 2022 to 2031. The Asia Pacific region is expected to witness the fastest growth in the used car market during this period, with a CAGR of approximately 7.7%. This growth is fueled by the rapid increase in income, high demand for cars, and the proliferation of classified car platforms and dealership certified pre-owned (CPO) programs (Waske & Katare, 2023).

Another trend that is seen in the used car industry is the rise of electric vehicles (EVs) in reshaping the market, with more used electric and hybrid cars becoming available. However, the residual values of gasoline cars are declining as the market shifts towards electric mobility (GoMechanic, 2024). Online platforms like Carvana and Vroom have revolutionized the market by making it easier to buy used cars digitally, complete with virtual tours and financing options and Certified Pre-Owned (CPO) programs are increasing popularity of used cars, offering buyers quality, reliability and transparency through inspected and refurbished vehicles (Grand View Research, 2023).

The semiconductor chip shortage has limited new car production, driving up demand and prices for used cars. The average age of vehicles on the road is increasing, boosting demand for used car parts and maintenance services. Sustainability concerns are also pushing consumers towards more environmentally friendly used vehicles, such as EVs and hybrids (Spyne, 2024).

The proliferation of shared mobility services like Ola and Uber is expected to reduce overall car ownership, impacting the used car market by decreasing the demand for personal vehicles (McKinsey & Company, 2023). These trends highlight a dynamic used car market influenced by economic, technological, and environmental factors.

4.2.3 National trends and patterns in used car industry

The number of motor vehicles in operation in Nepal surpassed 3.1 million, according to a report by the Department of Transport Management (DOTM) in April 2017/18. The report further reveals a substantial increase from 88,735 registered motor vehicles in FY 2006/07 to 444,259 units in FY 2016/17, demonstrating a fivefold rise over a decade and highlighting the growing demand for automobiles in Nepal. Additionally, the Nepal Automobile Dealers Association (NADA) notes that the automobile sector contributes Rs 100 billion in taxes to the national treasury annually, though the specific tax contributions of the used car industry remain undetermined. This market expansion is not only improving the quality of life for Nepalese but also bolstering the country's economic growth (Poudel, 2018).

Reflecting international trends, Nepal's used car market is experiencing significant changes driven by economic conditions, technological progress, and evolving consumer preferences. Economic uncertainties and variable remittance inflows make used vehicles more appealing compared to new ones (Nepal Rastra Bank, 2022). High import duties on new cars also enhance the attractiveness of used vehicles (Ministry of Finance, 2022). The global shortage of semiconductor chips has led to increased prices and demand for used cars (Kuhnert et al., 2018). Rising fuel prices and environmental concerns are boosting interest in hybrid and electric vehicles (Nepal Electricity Authority, 2023). Furthermore, online platforms like Hamrobazar and nepalicars.com have streamlined the buying and selling process, offering better access to information and competitive pricing (The Kathmandu Post, 2024).

4.2.4 Policy Recommendations

Policy recommendations for pricing of used cars have been extensively analyzed in the literatures. Studies suggest implementing standardized valuation frameworks to enhance market transparency and consumer trust. For instance, Kotler et al. (2020) advocate for a centralized database that aggregates historical sales data, ensuring accurate and fair pricing. Similarly, Ng and Yee (2018) emphasize the need for regulatory oversight to prevent fraudulent practices, suggesting that third-party inspections could serve as a deterrent to dishonest sellers. Moreover, Jiang and Qu (2021) propose incentivizing dealerships to adopt eco-friendly practices, which could also influence the pricing strategies of used cars by incorporating environmental factors. Kihm and Vance (2016) suggested government initiatives that can encourage the purchase of fuel-efficient used cars, potentially through tax breaks or rebates can be introduced by understanding the fuel efficiency of cars. This could significantly reduce overall fuel consumption and emissions in the transportation sector. Similarly, Erdem and Şentürk (2009) recommends car traders and platforms to look for the better characteristics that can influence price to a higher extent to increase their bargain. Anderson (2005) suggests that people don't consider the safety of vehicles as a price premium, so the government must implement traffic regulations for maintaining higher levels of safety from the traffic rules. These recommendations collectively aim to stabilize the market and protect consumer interests through comprehensive regulatory mechanisms.

4.3 Descriptive statistics and distribution patterns of variables

4.3.1 Descriptive Statistics of Variables

Table 2
Descriptive Statistics of variables in the dataset

Variables	**Mean**	**SD**	**Description**
Price	24,11,397	22,98,834	Price in NPR
Age of Vehicle	9.2	5.87	Vehicle Age in year
Mileage	57680.3	39056.47	Vehicle Speedometer reading (KM)
Fuel	0.76	0.43	Dummy equal 1 if Petrol Engine
Gearbox	0.78	0.41	Dummy equal 1 if car has Manual Gear
Drive	0.22	0.42	Dummy equal 1 for 4WD
Brands			
Ford	0.084	0.278	1 if the brand is Ford, 0 otherwise
Hyundai	0.280	0.449	1 if the brand is Hyundai, 0 otherwise
Kia	0.06	0.24	1 if the brand is Kia, 0 otherwise
Mahindra	0.059	0.236	1 if the brand is Mahindra, 0 otherwise
M. Suzuki	0.252	0.434	1 if the brand is a Suzuki, 0 otherwise
Nissan	0.041	0.197	1 if the brand is Nissan, 0 otherwise
Tata	0.077	0.267	1 if the brand is Tata, 0 otherwise
Volkswagen	0.043	0.203	1 if the brand is Volkswagen, 0 otherwise
Toyota	0.075	0.264	1 if the brand is Toyota, 0 otherwise
Renault	0.029	0.167	Reference Category
Color			
White	0.197	0.398	Reference Category
Black	0.024	0.153	1 if the color is Black, 0 otherwise
Blue	0.065	0.246	1 if the color is Blue, 0 otherwise
Brown	0.029	0.167	1 if the color is Brown, 0 otherwise
Gray	0.164	0.370	1 if the color is Gray, 0 otherwise

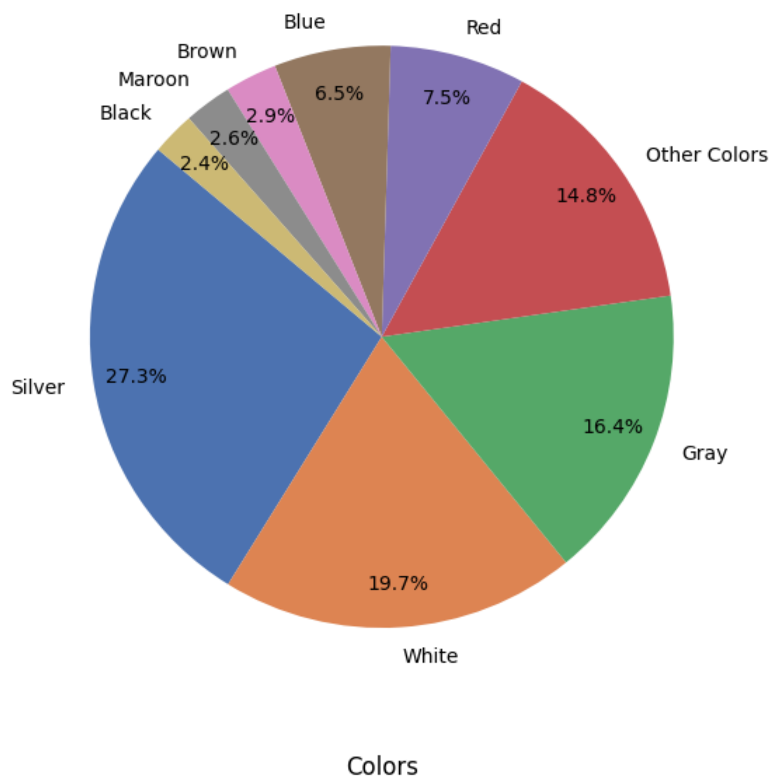
Maroon	0.026	0.160	1 if the color is Maroon, 0 otherwise
Red	0.075	0.263	1 if the color is Red, 0 otherwise
Silver	0.273	0.446	1 if the color is Silver, 0 otherwise
Other Colors	0.197	0.398	1 if the color is Other Colors, 0 otherwise
Body Type			
Hatchback	0.414	0.493	1 if the Body is Hatchback, 0 otherwise
SUV	0.373	0.484	1 if the Body is SUV, 0 otherwise
Sedan	0.109	0.312	1 if the Body is Sedan, 0 otherwise
Pickup	0.07	0.255	1 if the Body is Pickup, 0 otherwise
Van	0.033	0.178	This is reference Category
Engine (cc)			
Engine 1 (0-1000)	0.176	0.381	This is reference Category
Engine 2 (1001-1500)	0.539	0.499	1 if the Engine Capacity lies between 1001-1500, 0 otherwise
Engine 3 (1501-2000)	0.151	0.358	1 if the Engine Capacity lies between 1501-2000, 0 otherwise
Engine 4 (2001-2500)	0.065	0.247	1 if the Engine Capacity lies between 2001-2500, 0 otherwise
Engine 5 (2501-2900)	0.037	0.188	1 if the Engine Capacity lies between 2501-2900, 0 otherwise
Engine 6 (2901-above)	0.033	0.178	1 if the Engine Capacity lies between 2900+, 0 otherwise
Total No of Observations:		2045	

Source: Appendix-B

Table 2 makes a comprehensive overview on various characteristics or attributes of used cars in the dataset. From the table it can be comprehended that the average price of cars in the dataset is Npr. 24,11,397 and the average age of vehicle is 9.2 years. The average odometer reading (mileage) for the vehicles in the dataset is around 57,680 kilometers. Analyzing the dataset, it can be seen that the Petrol cars are more dominant with two-third of the total cars in the dataset i.e. (76%). Likewise, 78% of cars have two-wheel drive and similarly 78% of total cars are with Manual Gearbox. Similarly, more than half i.e. 53% of cars brands are either Hyundai or Maruti Suzuki. In Regards to body type the dominance of hatchbacks (41%) and SUVs (37%) suggests a possible preference for practical, versatile cars. Hatchbacks offer a good blend of size and functionality, while SUVs provide a combination of passenger space, cargo capacity, and potentially some off-road capability. Similarly, in terms of engine preferences, vehicles with engine capacities between 1001-1500 cc dominate the dataset, indicating a preference for vehicles with moderate engine power and fuel efficiency. Vehicles with larger engine capacities (2001-2900+ cc) are less common, possibly appealing to buyers seeking higher performance or towing capabilities.

4.3.2 Distribution of Colors

Figure 2
Distribution of colors in the dataset



Source: Appendix-B

The dataset in this study shows that that Silver cars are the most common with 27.3% of total datasets of color and the second one being white i.e. 19.7%. Similarly, gray with 16.4%, Cumulatively, all these colors i.e. gray, white, and silver are considered to be Neutral, and a total of them accounted for more than 60% of total datasets, which indicates that people generally prefer neutral colors then their counterparts. At the other end of spectrum is that Black, Brown and Maroon are colors with lowest density in our datasets.

Cultural preferences and regional trends can influence color choices. For example, white might be preferred for its association with cleanliness or status in some cultures or silver may be chosen for the possibility to hide the dust or dirt easily. From the dataset it can be seen that white, silver, and gray are the most preferred colors among buyers of used vehicles in the dataset. It can also be analyzed on the basis of color neutrality but further more datasets and more research must be done to conclude these analyses in datasets (Doležalová, 2020).

4.3.2 Correlation between variables

Table 3
Correlation between Continuous Variables

	Price	**Age**	**Mileage**
Price	1.0	-0.30	-0.13
Age	-0.30	1.0	0.39
Mileage	-0.13	0.39	1.0

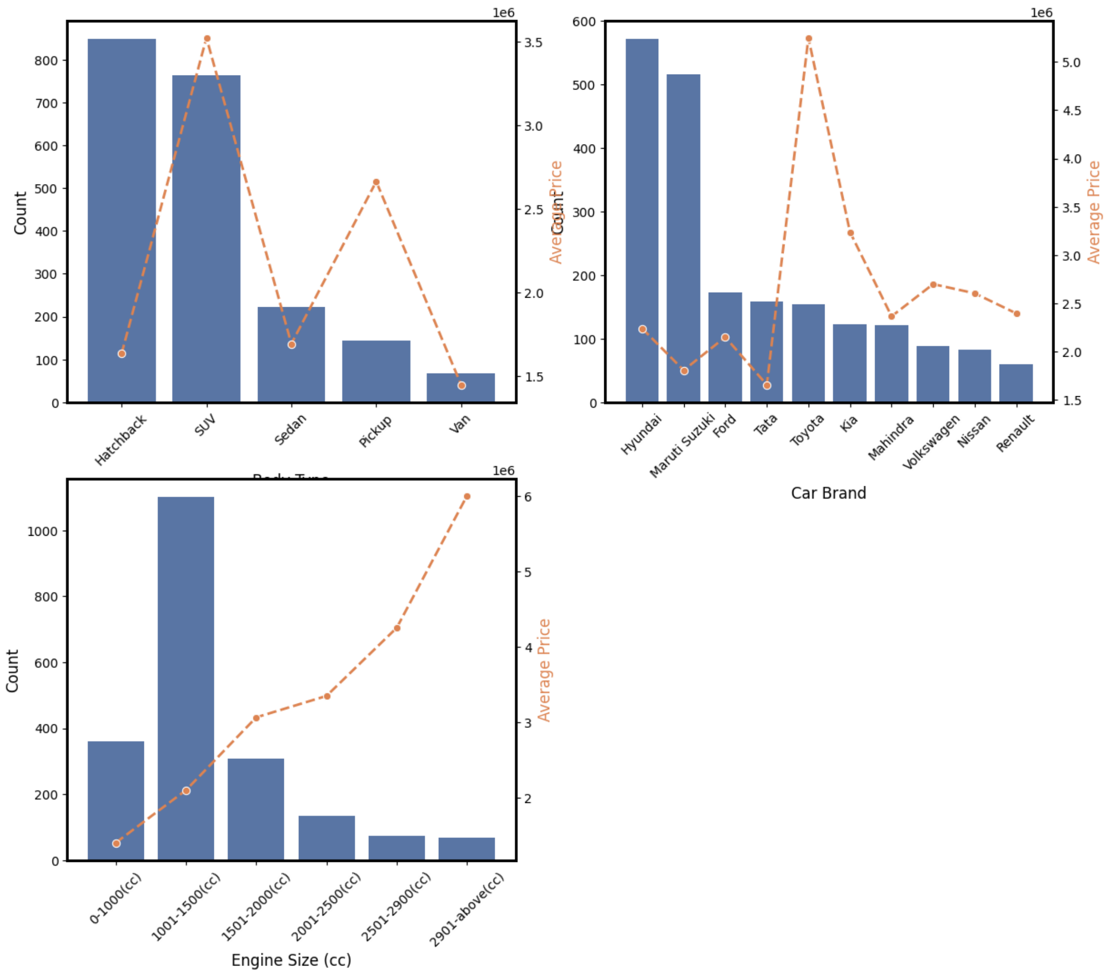
Source: Appendix-B

The findings from the correlation table 3, highlights that age is a significant factor in determining the price of used cars with a correlation value of -0.3, which indicates that age of car is inversely related to its price. Similarly, Mileage also correlates to Price negatively albeit to a lesser extent i.e. -0.13. Since, the direction of mileage with price is also negative, we can depict that price of car decreases as the mileage of car increases. Hence, the price of car is negatively associated with both of variables age and mileage in this data set.

4.3.3 Car Price Variations by Brand, Body Type, and Engine Size

Figure 3

Relationship of Car Body, Brand, Engine size with Average Price



Source: Appendix-B

The graphical representation in Figure 2, reveals several key insights of the datasets. SUVs and Hatchbacks dominate in popularity, with SUVs generally fetching higher prices followed by Pickup, Sedan, Hatchback and Van. The average price of an SUV car is seen to be NPR 35 Million while the average price of the lowest category i.e. van is lower than 1. 5Million. Hence there is significant price difference between different vehicle types which can clearly explains that the pricing of a car can be one of the important factors or characteristics which can explain the explanatory variable for pricing of used car.

Toyota and Kia are the most expensive brands but their presence is low while Tata and Maruti Suzuki are the most affordable brands. The interesting part is that both Tata and Maruti Suzuki are both of the Indian Origin brand. It also can be depicted that people in general prefer budget-friendly car models in Nepal i.e. Hyundai and Maruti Suzuki combined in total penetrates over 50% of the market share. Toyota being the expensive brand has an average price of around 5Milllion rupees while Tata being the cheapest brand with an average price of only 1.7Million. It can be seen a huge difference in the price of vehicles. Renault and Nissan are the car brands that make up the lowest percentage of all in the dataset. i.e Renault only covers only 2% of overall data while Nissan and Volkswagen 4% of overall dataset.

The graph also shows that engine size significantly influences pricing, with larger engines (2001-3000cc) being less common but are more expensive. The nature of data in this current analysis is that the car with engine range of 1000-1500 cc is more than 50% of total data sets. Similarly, it can also be understood that users are more interested in the average size of the engine, it might be because of cost as well as efficiency of the car starts decreasing as the size of engine increases.

4.4 Determinants of used car pricing

To achieve the objective of analyzing the determinants of used car pricing in Nepal, this study employs an Ordinary Least Squares (OLS) regression model, utilizing both semi-log and Box-Cox transformations. The semi-log transformation involves taking the natural logarithm of the dependent variable (price), which helps stabilize variance and interpret the relationship between the independent variables and price as multiplicative. The Box-Cox transformation is a flexible method that identifies the optimal power transformation to stabilize variance and normalize the distribution. These transformations enhance the model's robustness and interpretability. The independent variables include numeric factors such as mileage and age, as well as categorical factors such as fuel type, gearbox type, drive type, brand, body type, color, and engine capacity. The regression analysis aims to quantify the impact of each variable on car prices, with the semi-log model allowing percentage change interpretation and the Box-Cox model optimizing the functional form. This comprehensive approach helps elucidate the relative importance of different car attributes, contributing to a more transparent and equitable pricing mechanism in Nepal's used car market.

Table 4
Results of Semi -Log and Box Cox Transformation

Variable	Semi-Log		Box Cox Model	
	Coefficient	**P>|t|**	**Coefficient**	**P>|t|**
Constant	14.25	0.00	8.33	0.00
Age	-0.06	0.00	-0.02	0.00
Mileage	$-8.468*10^{-7}$	0.00	$-2.263*10^{-7}$	0.00
Fuel	-0.10	0.00	-0.03	0.00
Drive	0.09	0.00	0.02	0.00
Gearbox	0.03	0.41	0.01	0.23
Renault	Reference Brand			
Ford	-0.10	0.07	-0.04	0.04
Hyundai	0.13	0.02	0.03	0.03
Kia	0.12	0.05	0.03	0.16
Mahindra	-0.37	0.00	-0.12	0.00
Maruti Suzuki	0.07	0.18	0.02	0.30
Nissan	0.11	0.08	0.03	0.13
Tata	-0.50	0.00	-0.16	0.00
Toyota	0.56	0.00	0.15	0.00
Volkswagen	0.36	0.00	0.10	0.00
White	Reference Color			
Black	-0.02	0.79	0.00	0.92
Blue	0.03	0.48	0.00	0.21

Variable	Semi-Log		Box Cox Model	
Brown	-0.01	0.91	0.00	0.38
Gray	0.03	0.30	0.01	0.99
Maroon	0.00	0.998	0.00	0.98
Red	-0.03	0.38	-0.01	0.43
Silver	0.03	0.25	0.01	0.19
Other Color	-0.03	0.38	-0.01	0.52
Van	Reference Body Type			
Hatchback	0.40	0.00	0.13	0.00
SUV	0.70	0.00	0.21	0.00
Sedan	0.34	0.00	0.11	0.00
Pickup	0.18	0.00	0.06	0.00
0-1000(cc)	Reference Engine			
1001-1500	0.29	0.00	0.09	0.00
1501-2000	0.49	0.00	0.15	0.00
2001-2500	0.77	0.00	0.24	0.00
2501-2900	0.81	0.00	0.24	0.00
2901-above	0.98	0.00	0.29	0.00

Source: Appendix-B

The adjusted R square value in the semi log model in the given data set shows that the variation of explanatory variables explains 68.2 percent of the variation in the prices of cars. The F-statistic of 157.1 with a low p-value (0.0) and Probability of Omnibus Test (0.00) indicates that the model is statistically significant and good fit to data. The Model shows that the color, gearbox and few brands are not significant at 5% level of significance. While most of the other variables are significant at 5% level of significance (see Appendix A, Table A for detailed results).

The Age of car with coefficient of -0.06 indicates that for every one-unit increase in age of car (years), the predicted price of car decreases by approximately 6%, holding all other variables constant. It can also be considered as the rate of depreciation of cars on a year to year basis. Similarly, Mileage also shows similar trend as that of age i.e. the price of a car decreases as mileage increases, while the coefficient of mileage being too small, it indicates a lesser impact of mileage on the price (see Appendix A, Table A for detailed results).

Another interesting result found from the study is that the car with diesel engines are 10% more expensive than its counterpart petrol which is given by the coefficient -0.10. Similarly, the 4WD i.e. four-wheel drive vehicles are more expensive than a 2WD vehicle by approx. 9% which is defined by the coefficient of 0.09. With regards to brand Toyota, Volkswagen and Hyundai are more expensive then the reference brand (Renault). Toyota with coefficient 0.56 appears to be the most expensive car brands among the sample brands, they are predicted to have prices approximately 56% higher than the reference car brand. Likewise, Volkswagen, with a coefficient of 0.36 shows that it is the second highest brand with price 36% higher than that of Renault. In contrast, Tata cars with coefficient of -0.50 are predicted to have prices approximate 50% lower than the reference brand and Mahindra also seems to be cheaper than the reference brand.

Among the different car body type the study found that, Van is the cheapest among all. While the SUV are expensive body type. The SUV with the coefficient of 0.70 shows that SUVs are almost 70% expensive than the reference brand i.e. Van, which is followed by Hatchback. The positive coefficients of engine ranges suggest that cars with larger engine capacities are predicted to have higher prices. The data presented shows that price is directly related with the size of engine in the car. From our dataset, car with engine size of 2900+ cc has a coefficient of 0.98 indicates that the price of lowest size engine cars is 98% cheaper than the highest engine size used in the study. Likewise, the immediate engine size of 2501-2900cc are 81% more expensive than cars, which is indicated by the coefficient of 0.81.

In contrast, some variables are found to be insignificant, brands like Ford, Nissan, Maruti Suzuki and other features like Gearbox and Color are seen to be statistically insignificant, this does not mean they don't impact the price but there's no clear evidence that having an automatic or a manual gearbox or car being of any color affects the price of used car (see Appendix A, Table A for detailed results).

The Box-Cox Transformation result demonstrates that, the adjusted R-squared value in Box-Cox transformation indicates that, approximately 68.3 percent of the variability in car prices can be accounted by the variation in explanatory variables. With an F-statistic of 143 accompanied by a negligible p-value of 0.0 and a Probability of Omnibus Test of 0.00, suggests that the model exhibits statistical significance and demonstrates a strong fit to the data. With Box-Cox model most of the variables are significant at 5% level of significance, while few variables including some brands i.e. Kia, Nissan, Maruti Suzuki along with Gearbox and Color are found to be insignificant (see Appendix A, Table B for detailed results).

This model shows that the age of the car has a significant impact on its price in the model. The negative coefficient of -0.02 indicates that cars tend to depreciate over time. While, coefficient of variable in semi log model could be interpreted, the direction and intensity of box-cox model can be analyzed but actual meaning from this transformation requires complex back transformation and hence it is not used to interpret the value of coefficient. Similar to the age variable, the coefficient of mileage is negative but it is very low, which indicates that as mileage of car increases, the price of the car decreases but at a very low intensity. Other interesting insights are very similar to the semi log model i.e. Fuel variable with a coefficient of -0.03 are depict that Diesel being a reference brand are more expensive than their counterpart i.e. petrol engine. Similarly, 4WD (wheel drive) car in this case being the reference brand and 4WD car with a coefficient of 0.02 are more expensive than their reference category 2WD. Likewise, as similar to the semi log model, Hatchbacks, Sedans, and Pickups cars all seem to command higher prices compared to Vans which is the reference category in this model. This suggests that consumers might be willing to pay more for the features and functionalities these body styles offer.

Additionally, it is seen from the table above that Hyundai (0.03), Toyota (0.56), Volkswagen (0.10) are more expensive than Renault while Tata (-0.16), Mahindra (-0.11) and Ford (-0.04) are less expensive on average. Moreover, Cars with larger engine sizes (all categories from 1001 cc and above) are predicted to cost more than those with smaller engines (reference category being 0-1000cc) which is explained by the coefficient of variables in above table i.e. the coefficient of all the ranges being positive and greater than 0 indicates that the reference engine capacity is the most affordable one. This makes sense as larger engines typically offer more power and performance, which can be a deciding factor for some car buyers (see Appendix A, Table B for detailed results).

In comparison of two functional forms, the semi log and Box-cox transformation model, both models demonstrate a strong fit to the data with adjusted R-squared values of 68.2 % and 68.3 % respectively. The semi-log model, with an F-statistic of 157.1, and the Box-Cox model, with an F-statistic of 143, both exhibit statistical significance with p-values of 0.00. Both models identify key determinants of car prices, including variables like age, mileage, fuel type, drive type, and specific car brands such as Hyundai, Mahindra, Tata, Toyota, and Volkswagen, as significant factors (see Appendix A, Table A and Table B for detailed results).

Similarly, both models agree that the color of car and type of gearbox (manual vs automatic) and few of models are insignificant in influencing car prices. In contrast, the Box-Cox model suggests a slightly weaker influence of age on price depreciation, with a coefficient of -0.0189 compared to -0.0623 in the semi-log model. Both models evident that cars with larger engine capacities and body styles such as hatchbacks, sedans, and pickups command higher prices compared to the reference categories (see Appendix A, Table A and B for detailed results).

Overall, the comparative analysis of the semi-log and Box-Cox models highlights their strong fit for data and consistency in identifying significant predictors of used car prices, while also reinforcing the negligible impact of color and gearbox and few of the models on car valuations.

4.4.1 Tests of Multicollinearity

Since the model has a Condition number i.e.$1.41*10^{06}$ (see Appendix A, Table B), it is seen that both models do not transform independent variables, indicating that there might have some level of multicollinearity between the independent variables. To confirm if we need to treat for reducing multicollinearity issue in the model, the study tested for the presence of multicollinearity using Jarque-Bera in both of the models. Presence of Multicollinearity indicates the residuals (errors) are not normally distributed which is against the basic assumption of regression. So, to further confirm the severity of multicollinearity of variables VIF is computed. The table below explains the VIF value for various variables.

Table 5
VIF factor for Dependent Variables

Variables	**VIF**	**Severity**
Mileage	1.36	Low
Fuel	2.22	Low
Drive	1.77	Low
Gearbox	1.13	Low
Age	1.44	Low
Mileage	1.36	Low
Fuel	2.22	Low
Drive	1.77	Low
Gearbox	1.13	Low
Age	1.44	Low
Ford	3.93	Low
Hyundai	8.83	Moderate
Kia	3.19	Low
Mahindra	3.72	Low
Maruti Suzuki	7.95	Moderate
Nissan	2.55	Low

Variables	VIF	Severity
Tata	3.76	Low
Toyota	4.22	Low
Volkswagen	2.76	Low
Black	1.15	Low
Blue	1.30	Low
Brown	1.17	Low
Gray	1.68	Low
Maroon	1.19	Low
Red	1.34	Low
Silver	1.89	Low
Other Color	1.58	Low
Hatchback	8.70	Moderate
SUV	8.74	Moderate
Sedan	4.27	Low
Pickup	3.80	Low
1001-1500	2.45	Low
1501-2000	2.66	Low
2001-2500	2.23	Low
2501-2900	2.02	Low
2901-above	1.71	Low

Source: Appendix-B

Since most of the variables has a VIF factors with low presence of multicollinearity while very few i.e. Brands (Hyundai, Maruti Suzuki) and Body Type (SUV and Hatchback) indicates having moderate level of multicollinearity issue as shown in table above. Since, none of the variables are seen to have strong or severe multicollinearity issue, while very few with moderate issue. The conclusion is seen that the multicollinearity issue may not affect the model's predictive performance significantly.

Hence, it can be concluded that the multicollinearity issue does not affect the performance of the model to much extent so no further treatment is necessary.

4.5 Discussions

The current study used a hedonic model for explaining pricing of a used car based on its various characteristics. This study includes analysis of Semi log as well as Box-cox transformation. Both of the transformations found that the variables make similar goodness-of-fit measures. The Box-cox transformation was used specially to stabilize variance and make data normally distributed; its complexity of interpretation makes it hard to analyze for each coefficient of explanatory variables (Maurer et al., 2004).

In the semi logarithmic model, the dependent variable (price) is transformed into the logarithmic value while independent variables remain the same. The semi log model in itself explains that the coefficient from the result represents the percentage change in the dependent variable for a one-unit change in the independent variable, assuming all other variables in the model remain constant. While each individual coefficient is not much interpretable in case of Box cox model, whose value depends on the value of Lambda. The result shows that both of the models i.e. semi-log and box-cox transformation shows similar performance in terms of explanatory power and statistical significance. However, Box-cox transformation exhibits a slightly better fit as indicated by Lower value of AIC and BIC values (see Appendix A, Table A, B for detailed results).

Based on the provided Box-Cox transformation result with a lambda value of approximately -0.0832, the regression model was estimated using maximum likelihood estimation method across a range of lambda values from -1 to 1 in increments of 0.1. The specific lambda value yielding the highest log likelihood, approximately -0.0832, was selected for the model. When assessing the model against alternative models such as semi-logarithmic using likelihood ratio (LR) test statistics, it was observed that the null hypothesis was rejected, indicating that the Box-Cox transformed model provides a superior fit to the data. The same outlook result was found from various studies like one by Erdem and Şentürk (2009) and another by Shiratsuka (1995), who found that box-cox functional form had better fit for data. Yayar (2018) and Doležalová (2020) also found a semi log model to the choice of their functional form of regression. VIF test also explains that very few variables i.e. only categorical variables had multicollinearity problems with only moderate severity level while, most of the variables having low level of multicollinearity, hence the further treatment of variables was not necessary (see Appendix A, Table B for detailed results).

Based on variables, Yayar (2018) found out that age is the most important variable that decreases the price of a used car. Similar finding was done on this study. The study suggested that the age reduces the price of a car by 6.23%, which was very closer to the study made by Kihm and Vance (2016) which was 7.4%, while another study by Doležalová (2020) found that the price of used car decreases by 9.3%. As the age of car increases, their value decreases, which is a common trend in the automotive market due to factors such as wear and tear, technological advancements, and changes in consumer preferences.

The Mileage or Odometer reading although has a negative influence, which is also backed by studies like Kihm and Vance (2016) and Doležalová (2020), on the pricing of car but the current study shows that the effect of the mileage is seen to be very low impact, which was closer to study done by Balce (2016) who found out that mileage is insignificant to the pricing. Balce explains that it might be because of the possibility of two-way interaction effects with other factor like age.

Similarly, the study also revealed that Diesel engines are almost 10% more expensive than the Petrol engine cars. The result was similar to other studies like one by Erdem and Şentürk (2009), and another by Yayar (2018) who found that Diesel engines are almost 20% more expensive. Likewise, various brands perform differently, and they are region specific. Toyota and Volkswagen are the most expensive brands in Nepal which are supported by both models Box-cox and Semi log models. SUV is the most expensive type of body in Nepal and Van is the cheapest of all. This suggests that consumers might be willing to pay more for the features and functionalities these body styles offer.

Engine Capacity or Power is directly proportional to the price of a car, the higher the engine capacity the higher is the price of the car. This explains that the higher the power of a car, the higher the price for its performance. The highest engine size of 3000cc is almost 10% higher than that of reference category 1000 cc. The similar trend in case of engine capacity and price was seen in study by Kihm and Vance (2016) and Doležalová (2020).

Balce (2016) found that car color has no significant impact on pricing of cars. Both of the functional forms of this study also found that color is not significant to explain that the pricing of a car is dependent on its color. Similarly, a few car models and Gearbox in this study found that they are insignificant even at 10% level of significance, such that they cannot explain the price variations of a used car even though it might impact the pricing so, it cannot for sure explain if they actually impact the pricing of used cars. The gearbox, in contrast to this study by Erdem and Şentürk (2009), Doležalová (2020) found that automatic gearboxes are more expensive than their manual counterparts.

CHAPTER V

SUMMARY AND CONCLUSIONS

5.1 Introduction

This study is concerned with evaluation of pricing of used cars based on the roles of various characteristics of a car. This chapter summarizes and concludes the overall study and provides some policy recommendation and implication strategies which can support policy maker to improve the transparency of car market.

5.2 Summary

The study is about the price determination of used vehicles in Nepal. The study used was hedonic pricing model in order to explain the pricing of used cars by determining the impact of each of the associated features of a car. The explanatory variables used in the model are Age of Vehicle, Mileage, Fuel, Drive Wheel, Gearbox, Color, Brand, Body of Car, Engine (cc). The study used 2045 datasets collected from Nepal's renowned classified ads platform hamrobazar.com and nepalicars.com. Previous literatures have predominantly favored logarithmic transformations in similar studies, with few exceptions employing linear models or Box-Cox transformations. This study also explored both Semi-Log and Box-Cox transformations, which revealed comparable goodness-of-fit measures. While the Box-Cox transformation helps in stabilizing variance and normalizing data distribution, its interpretational complexity is a challenge in coefficient analysis. In this analysis, both Semi-Log and Box-Cox transformations displayed a similar explanatory power and statistical significance. However, the Box-Cox transformation demonstrated a slightly superior fit, indicated by lower AIC and BIC values.

Following are the findings of the study:

- Age emerged as a crucial determinant, showing a negative relationship with price, implying depreciation over time.
- Mileage displayed a negative correlation, but having a minimal impact on price.
- Fuel type, Drive, and certain brands exhibited significant effects on pricing

- Body types such as Hatchbacks and SUVs are more expensive than a van, reflecting consumer preferences over comfort
- Engine capacity correlates with higher prices, indicating demand for enhanced performance.
- Despite having low multicollinearity, model demonstrates robust predictive performance
- Diesel cars are 10% more expensive than Petrol Cars
- 4-Wheel drive seems to be 9% expensive than 2-Wheel drive.
- Factors like Gearbox, Color and few brands appeared to be insignificant in both of the models.

Despite the presence of multicollinearity, the predictive performance of the model remains largely unaffected. While further improvements in model robustness are desirable, the current analysis provides valuable insights for stakeholders in the used car market.

5.3 Conclusions and Policy Implication

This study covers the importance of comprehensive modeling techniques in understanding price determinants in the secondary car market. By incorporating various intrinsic characteristics, the hedonic model offers a nuanced perspective on pricing dynamics, facilitating informed decision-making for consumers, dealers, and policymakers alike. Few policy recommendations are also made within the study, implementing and addressing these recommended policies, this study can contribute to a more transparent, efficient, and consumer-friendly used car market in Nepal and also can contribute to existing knowledge gap.

The developed pricing model can equip consumers with a data-driven tool to estimate the fair value of used cars. This can help them negotiate better deals and avoid potential price manipulation by unethical sellers. Increased transparency in pricing fosters trust in the used car market. Consumers can approach purchases with more confidence, knowing they have reliable information to base their decisions on can help improve market efficiency.

Based on the findings of this study, several policy recommendations are proposed to enhance the used vehicle market in Nepal. Establishing a centralized vehicle information system from initiative of either a government or dealer association can improve market transparency, reduce information asymmetry and space for growth of innovation within the industry. Introducing certification programs and offering incentives for regular maintenance can ensure better vehicle conditions and trust with the dealer. Providing incentives for eco-friendly vehicles, such as tax breaks, and supporting financing options through partnerships between financial institutions and dealerships can further enhance affordability with promotion for fuel efficient vehicle. Developing a government-endorsed depreciation guide can help consumers make informed decisions. Enhanced dealer regulations and the promotion of digital platforms for used vehicle transactions can ensure fair practices and facilitate easier price comparisons. Finally, public awareness campaigns can educate consumers on evaluating used vehicles, understanding pricing determinants, and recognizing their rights under consumer protection laws. These measures can collectively foster a more transparent, efficient and consumer-friendly used vehicle market in Nepal.

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APPENDIX

APPENDIX – A

Table A

Result of Semi log Transformation and OLS Regression result

Dep. Variable:	PRICE	R-squared:	0.686
Model:	OLS	Adj. R-squared:	0.682
Method:	Least Squares	F-statistic:	142.2
Date:	Sun, 07 Jul 2024	Prob (F-statistic):	0.00
Time:	22:49:43	Log-Likelihood:	-834.02
No. Observations:	2045	AIC:	1732.
Df Residuals:	2013	BIC:	1912.
Df Model:	31		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	14.2512	0.076	188.347	0.000	14.103	14.400
MILEAGE	-8.468e-07	2.42e-07	-3.493	0.000	-1.32e-06	-3.71e-07
FUEL	-0.1016	0.028	-3.586	0.000	-0.157	-0.046
DRIVE	0.0791	0.026	3.050	0.002	0.028	0.130
GEARBOX	0.0171	0.021	0.817	0.414	-0.024	0.058
AGE	-0.0623	0.002	-37.552	0.000	-0.066	-0.059
Ford	-0.1047	0.058	-1.807	0.071	-0.218	0.009
Hyundai	0.1309	0.054	2.438	0.015	0.026	0.236
Kia	0.1205	0.061	1.971	0.049	0.001	0.240
Mahindra	-0.3861	0.066	-5.823	0.000	-0.516	-0.256
Maruti Suzuki	0.0715	0.053	1.358	0.175	-0.032	0.175
Nissan	0.1149	0.066	1.753	0.080	-0.014	0.244
Tata	-0.4998	0.059	-8.482	0.000	-0.615	-0.384
Toyota	0.5551	0.063	8.794	0.000	0.431	0.679
Volkswagen	0.3552	0.066	5.346	0.000	0.225	0.486
Black	-0.0155	0.057	-0.273	0.785	-0.127	0.096
Gray	0.0292	0.028	1.028	0.304	-0.027	0.085
Blue	0.0265	0.038	0.703	0.482	-0.047	0.100
Brown	-0.0057	0.053	-0.108	0.914	-0.109	0.097
Maroon	0.0002	0.055	0.003	0.998	-0.108	0.108
Red	-0.0315	0.036	-0.884	0.377	-0.102	0.038
Silver	0.0290	0.025	1.159	0.247	-0.020	0.078
Other Colors	-0.0250	0.029	-0.871	0.384	-0.081	0.031
Hatchback	0.4001	0.049	8.242	0.000	0.305	0.495
Pickup	0.1825	0.062	2.945	0.003	0.061	0.304
SUV	0.6959	0.050	14.042	0.000	0.599	0.793
Sedan	0.3429	0.054	6.375	0.000	0.237	0.448
1001-1500(cc)	0.2942	0.025	11.549	0.000	0.244	0.344
1501-2000(cc)	0.4897	0.037	13.252	0.000	0.417	0.562
2001-2500(cc)	0.7688	0.049	15.665	0.000	0.673	0.865
2501-2900(cc)	0.8051	0.061	13.122	0.000	0.685	0.925
2901-above(cc)	0.9785	0.060	16.440	0.000	0.862	1.095

Omnibus:	787.542	Durbin-Watson:	1.431
Prob (Omnibus):	0.000	Jarque-Bera (JB):	12190.075
Skew:	1.387	Prob (JB):	0.00
Kurtosis:	14.635	Cond. No.	1.41e+06

Table B

Result of Box-Cox Transformation and OLS Regression result

Dep. Variable:	PRICE	R-squared:	0.688
Model:	OLS	Adj. R-squared:	0.683
Method:	Least Squares	F-statistic:	143.2
Date:	Mon, 08 Jul 2024	Prob (F-statistic):	0.00
Time:	07:43:05	Log-Likelihood:	1638.2
No. Observations:	2045	AIC:	-3212.
Df Residuals:	2013	BIC:	-3032.
Df Model:	31		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	8.3347	0.023	368.986	0.000	8.290	8.379
MILEAGE	-2.263e-07	7.24e-08	-3.127	0.002	-3.68e-07	-8.44e-08
FUEL	-0.0281	0.008	-3.321	0.001	-0.045	-0.011
DRIVE	0.0227	0.008	2.927	0.003	0.007	0.038
GEARBOX	0.0075	0.006	1.194	0.233	-0.005	0.020
AGE	-0.0189	0.000	-38.135	0.000	-0.020	-0.018
Ford	-0.0356	0.017	-2.059	0.040	-0.070	-0.002
Hyundai	0.0346	0.016	2.157	0.031	0.003	0.066
Kia	0.0258	0.018	1.415	0.157	-0.010	0.062
Mahindra	-0.1184	0.020	-5.983	0.000	-0.157	-0.080
Maruti Suzuki	0.0165	0.016	1.047	0.295	-0.014	0.047
Nissan	0.0297	0.020	1.515	0.130	-0.009	0.068
Tata	-0.1571	0.018	-8.932	0.000	-0.192	-0.123
Toyota	0.1542	0.019	8.183	0.000	0.117	0.191
Volkswagen	0.1028	0.020	5.184	0.000	0.064	0.142
Black	-0.0018	0.017	-0.106	0.916	-0.035	0.032
Gray	0.0105	0.008	1.242	0.214	-0.006	0.027
Blue	0.0098	0.011	0.871	0.384	-0.012	0.032
Brown	-0.0002	0.016	-0.010	0.992	-0.031	0.031
Maroon	0.0004	0.016	0.026	0.979	-0.032	0.033
Red	-0.0084	0.011	-0.789	0.430	-0.029	0.012
Silver	0.0098	0.007	1.310	0.190	-0.005	0.024
Other Colors	-0.0055	0.009	-0.636	0.525	-0.022	0.011
Hatchback	0.1250	0.014	8.625	0.000	0.097	0.153
Pickup	0.0620	0.019	3.350	0.001	0.026	0.098
SUV	0.213	0.015	14.403	0.000	0.184	0.242
Sedan	0.1088	0.016	6.778	0.000	0.077	0.140
1001-1500(cc)	0.0937	0.008	12.319	0.000	0.079	0.109
1501-2000(cc)	0.1517	0.011	13.752	0.000	0.130	0.173
2001-2500(cc)	0.2363	0.015	16.128	0.000	0.208	0.265
2501-2900(cc)	0.2421	0.018	13.216	0.000	0.206	0.278
2901-above(cc)	0.2916	0.018	16.414	0.000	0.257	0.326

Omnibus:	747.636	Durbin-Watson:	1.428
Prob (Omnibus):	0.000	Jarque-Bera (JB):	12029.118
Skew:	1.282	Prob (JB):	0.00
Kurtosis:	14.602	Cond. No.	1.41e+06

Lambda: -0.08319755830379594