

Exploring Online Auction Markets for Remanufactured Electronics Using Explainable Artificial Intelligence: Evidence from eBay

By

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Abstract

Despite the growing relevance of remanufactured goods in circular economy and closed-loop supply chains, existing literature has paid limited attention to online auction-based transactions, focusing predominantly on fixed-price markets, treating remanufactured products as a homogeneous category, and largely overlooking bidder heterogeneity and the nuanced role of product condition levels in signal-based pricing mechanisms. This thesis addresses this gap by examining online auctions for remanufactured electronics, with a focus on how seller-, buyer-, and platform-level signals influence auction outcomes, how these effects differ across product condition levels, and how bidder heterogeneity informs distinct bidding strategies and behaviours.

While market signalling has been widely studied in fixed-price contexts, its role in online auctions for remanufactured products remains underexplored. This study addresses this gap by comparing traditional linear regression (LR) with machine learning (ML) approaches to model final auction prices. Using a dataset from eBay, the analysis reveals that Random Forest outperforms LR models in predictive accuracy, confirming the non-linear and interaction-driven nature of pricing dynamics in this domain. Explainable Artificial Intelligence (XAI) technique, specifically, SHapley Additive exPlanations (SHAP), is used to enhance model explainability, identifying key predictors (e.g., feedback score, bid count, starting price and product images) and revealing their complex interactions. Notably, the study uncovers an asymmetric feedback effect and provides feature importance alongside insights into the joint influence of market signals. These results contribute to a better understanding of how auction prices are shaped by the interplay of seller, buyer, and platform-level signals in remanufactured product markets.

The second empirical study investigates how auction outcomes and the effectiveness of market signals vary across remanufactured product condition tiers: Excellent, Very Good, Good. Based on eBay transaction data, the findings reveal distinct behavioural and pricing patterns by condition level. Higher-condition items tend to be listed by less experienced sellers employing affective descriptions, low starting prices, and extensive visual content—strategies associated with higher final prices. Conversely, lower-condition items are offered by more experienced sellers who rely on functional signals but achieve lower price outcomes. This study is the first to systematically analyse condition-specific heterogeneity in auction prices for remanufactured products, offering new empirical evidence on the differential role of market signals by product condition.

The third empirical study explores bidder heterogeneity in remanufactured product auctions by extending the behavioural framework of Bapna *et al.* (2004) with additional variables such as feedback scores and average bid increments. Through K-means clustering followed by SHAP-enhanced XGBoost classification, the study identifies a new hybrid bidder type, Shooters, positioned between traditional Snipers and Participators. The approach provides interpretable, data-driven insights into the behavioural attributes that differentiate bidder segments. Findings indicate that Snipers exhibit the highest win rates and bidding efficiency, while Shooters also perform competitively, demonstrating the viability of adaptive hybrid strategies. This is the first study to empirically classify bidder behaviour in remanufactured product auctions, offering novel contributions to auction theory and bidder segmentation.

Collectively, by analysing the price effects of market signals, the influence of product condition, and bidder heterogeneity in online auctions, while integrating advanced ML and XAI

techniques, this research addresses key gaps in the literature on remanufactured product markets. These contributions enhance our understanding of consumer behaviour and pricing dynamics in auction environments marked by high information asymmetry, while also advancing theoretical discourse in remanufacturing, closed-loop supply chains, and data-driven operations research.

List of Publications

The following work was published / submitted for publication as a result of the investigations performed in the course of this thesis:

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Table of Contents

Table of Contents.....	1
List of Figures	1
List of Tables.....	1
Chapter 1.....	1
1.1 Background	1
1.2 Motivation.....	13
1.3 Research Objectives and Research Questions.....	15
1.4 Outline.....	18
Chapter 2.....	19
2.1 Introduction.....	19
2.2 Empirical Research on Consumer Behaviour Toward Remanufactured Products	20
2.3 Impact of Product Condition on Market Value and Consumer Perception	27
2.3.1 Comparison Between New and Remanufactured Products.....	27
2.3.2 Comparison Across Borad Product Condition Categories	28
2.3.3 Comparison of Detailed Product Condition Levels.....	31
2.4 Bidding Strategies in Online Auction.....	35
2.4.1 Heterogeneity in Online Bidding Strategy	35
2.4.2 Different Bidding Strategy by Experience	46
2.4.3 Explainable Clustering.....	56

2.5	Economic Theories	65
2.5.1	Information Asymmetry	65
2.5.2	Methods for Mitigating Information Asymmetry	70
Chapter 3		86
3.1	Introduction	86
3.2	Research Philosophy	87
3.3	Research Design.....	93
3.4	Research Method.....	102
3.4.1	Data Understanding.....	105
3.4.2	Data Preparation.....	107
3.4.3	Modelling	116
3.4.4	Model Evaluation	149
3.4.5	Model Deployment	161
3.5	Summary	174
Chapter 4		176
4.1	Introduction	176
4.2	Data Understanding	178
4.2.1	Data Description.....	178
4.2.2	Dependent and Explanatory Variables	180
4.2.3	Data Exploration	199
4.3	Data Preparation	202

4.3.1	Data Cleansing	202
4.3.2	Data Construction	204
4.3.3	Feature Selection.....	207
4.3.4	Data Scaling	212
4.4	Empirical Results	213
4.4.1	Evaluation of Predictive Model Performance.....	215
4.4.2	Model Deployment – Interpretation of Results	217
4.5	Robustness Check	235
4.6	Discussion and Managerial Implications	238
Chapter 5		242
5.1	Introduction.....	242
5.2	Data Understanding.....	243
5.2.1	Data Description	243
5.2.2	Dependent Variable and Explanatory Variables	245
5.2.3	Data Exploration	245
5.3	Data Preparation.....	248
5.3.1	Data Cleansing	248
5.3.2	Data Construction	249
5.3.3	Data Selection.....	250
5.3.4	Data Scaling	250
5.4	Empirical Results	251

5.4.1	Empirical Results by Condition.....	257
5.4.2	SHAP Dependence Plot and Interaction Effects	271
5.5	Discussion and Managerial Implications	279
Chapter 6		285
6.1	Introduction	285
6.2	Data Understanding	288
6.2.1	Data Description.....	288
6.2.2	Clustering Criteria	289
6.2.3	Data Exploration	294
6.3	Data Preparation	296
6.3.1	Data Cleaning	296
6.3.2	Data Construction	296
6.3.3	Data Scaling	299
6.4	Empirical Results and Discussions	300
6.4.1	Principal Component Analysis (PCA) results	301
6.4.2	K-means clustering results	303
6.4.3	Explaining the clustering results	311
6.4.4	Outcome Analysis	317
6.5	Discussion and Managerial Implications	325
Chapter 7		329
7.1	Introduction	329

7.2	Research Questions and Main Findings of the Study.....	329
7.3	Research Ethics	334
7.4	Contributions	335
7.5	Limitations of the Study and Future Directions	340
	List of Reference	344
	Appendix	386

List of Figures

Figure 3.1: The ‘Research Onion’ Framework.....	88
Figure 3.2: Framework of the Research Design.....	93
Figure 3.3: Overview of the CRISP-DM Process	104
Figure 3.4: Diagram of the K-Fold Cross-Validation Method.....	147
Figure 4.1: Overview of the Methodological Framework.....	177
Figure 4.2: Box Plots Showing Distribution of the Original Dataset.....	201
Figure 4.3: SHAP Summary Bar Plots of All Features for RF and XGBoost Models	211
Figure 4.4: Predictive Performance of Models on Training and Testing Sets	216
Figure 4.5: SHAP Summary Bar Plot for the <i>RF_Boruta</i> Model	218
Figure 4.6: SHAP Beeswarm Summary Plot for the <i>RF_Boruta</i> Model	219
Figure 4.7: SHAP Dependence Plots for the <i>RF_Boruta</i> Model.....	221
Figure 4.8: SHAP Dependence Plots with Interaction Effects for Each Feature	228
Figure 4.9: Prediction Results for Robustness Check	236
Figure 4.10: SHAP Summary Bar Plot for the Robustness Check Model	237
Figure 5.1: Box Plots Showing the Distribution of the Original Dataset.....	247
Figure 5.2: Box Plots Showing the Distribution of the Overall Dataset for Analysis	252
Figure 5.3: Results of Predictive Performances of Models on Training and Testing Sets....	254
Figure 5.4: SHAP Summary Bar Plot for the Overall Dataset.....	255
Figure 5.5: SHAP Beeswarm Summary Plot for the Overall Dataset.....	256
Figure 5.6: SHAP Summary Bar Plot for the Excellent Subset	261
Figure 5.7: SHAP Beeswarm Summary Plot for the Excellent Subset	261
Figure 5.8: SHAP Summary Bar Plot for the Very Good Subset	266
Figure 5.9: SHAP Beeswarm Summary Plot for the Very Good Subset	266

Figure 5.10: SHAP Summary Bar Plot for the Good Subset.....	270
Figure 5.11: SHAP Beeswarm Summary Plot for the Good Subset.....	270
Figure 5.12: SHAP Dependence Plots Showing Interaction Effects (Overall Dataset)	272
Figure 5.13: SHAP Dependence Plots Showing Interactions Effects with Condition (Overall Dataset)	276
Figure 6.1: Conceptual Research Framework.....	287
Figure 6.2: Box Plots Showing the Distribution of the Original Dataset	295
Figure 6.3: Box Plots Showing the Original Data Distribution after Box-Cox Transformation	299
Figure 6.4: Plots for Cumulative Explained Variance and Eigenvalue Criteria	302
Figure 6.5: Plots for Clustering Quality Metrics: Silhouette and Calinski-Harabasz.....	304
Figure 6.6: Visualisation of K-Means Clustering on PCA-Reduced Data (2D Projection) .	305
Figure 6.7: Mean Feature Values by Cluster	307
Figure 6.8: SHAP Beeswarm Summary Plots by Cluster.....	312

List of Tables

Table 2.1. Summary of Literature on Customer Behaviour Towards Remanufactured Products	25
Table 2.2: Summary of Literature Examining Various Product Conditions	33
Table 2.3: Summary of Literature on Bidder Heterogeneity in Online Auctions	44
Table 2.4: Summary of Literature on the Impact of Bidder Experience in Online Auctions..	54
Table 2.5: Summary of Literature on Explainable Clustering.....	63
Table 3.1: Prediction and Confusion Matrix	160
Table 4.1: Descriptive Statistics for the Original Dataset	200
Table 4.2: Correlation Matrix for the Dataset Used in Analysis	208
Table 4.3: Variance Inflation Factors for Each Variable	209
Table 4.4: Variance Inflation Factors After Feature Elimination.....	212
Table 4.5: Descriptive Statistics After Feature Elimination.....	214
Table 4.6: Descriptive Statistics for the Training and Test Datasets.....	215
Table 5.1: Descriptive Statistics for the Original Dataset	246
Table 5.2: Descriptive Statistics for the Overall Dataset Used in Analysis	251
Table 5.3: Descriptive Statistics for the Excellent Subset.....	259
Table 5.4: Descriptive Statistics for the Very Good Subset	264
Table 5.5: Descriptive Statistics for the Good Subset	268
Table 6.1: Descriptive Statistics for the Original Dataset	294
Table 6.2: Descriptive Statistics after Box-Cox Transformation	298
Table 6.3: Correlation Matrix of Clustering Criteria.....	301
Table 6.4: Descriptive Statistics for Key Clustering Criteria by Cluster	306
Table 6.5: One-way ANOVA Summary: Winning Proportions by Clusters	318

Table 6.6: Pairwise Comparison of Winning Proportions Across Clusters	319
Table 6.7: Winning Possibilities by Cluster	319
Table 6.8: One-way ANOVA Summary: Normalised Loss of Surplus by Clusters	321
Table 6.9: Pairwise Comparison of Normalised Loss of Surplus Among Clusters	321
Table 6.10: Normalised Loss of Surplus by Cluster	322
Table 6.11: One-way ANOVA Summary for Winning Efficiency by Clusters	323
Table 6.12: Pairwise Comparison of Winning Efficiency Among Clusters	324
Table 6.13: Winning Efficiency by Cluster	324
Table A.1: Comparison of Train-Test Split Ratios in Study 1 (random_state=23)	386
Table A.2: Comparison of Train-Test Split Ratios in Study 1 (random_state=11)	386
Table A.3: Comparison of Train-Test Split Ratios in Study 2	386
Table A.4: Results of Alternative Clustering Method: DBSCAN	387
Table A.5: Comparison of Train-Test Split Ratios in Study 3	387

Chapter 1

Introduction

1.1 Background

This section establishes the foundation of the study by outlining the central research problem and situating it within pertinent academic and practical contexts. It reviews prevailing trends and literature on e-waste, product recovery methods with particular emphasis on remanufacturing and recent developments in both the academic and industry concerning remanufactured products. Through this, it highlights unresolved questions and identifies critical theoretical and empirical gaps that this study aims to address, thereby informing the formulation of the research objectives and the methodological framework that follows.

Although technically distinct, terms ‘remanufacturing’ and ‘refurbishing’ are often used interchangeably in both practice and literature, with remanufacturing typically referring to a more rigorous process that restores a product to “like-new” condition (Abbey *et al.*, 2015; Frota Neto, Bloemhof and Corbett, 2016; Chen and Chen, 2019). Similar to prior studies, this research uses remanufacturing as a general term encompassing both remanufacturing and refurbishing, for simplicity and consistency. A strict distinction is made only when context or technical precision requires it.

Increasing Waste of Electrical and Electronic Equipment (WEEE)

The growth of Waste Electrical and Electronic Equipment (WEEE, or e-waste) has emerged as a critical global concern, standing as the fastest-growing waste stream worldwide (International Labour Organization, 2014). The situation has only worsened since then. In 2022, global e-waste generation reached 62 million metric tonnes (Mt) exceeding the earlier estimate of 59.4 Mt for the same year (Forti *et al.*, 2020) and is projected to rise to 82 Mt by 2030 (Baldé *et al.*, 2024). This accelerating growth underlines the urgent need for more effective e-waste management strategies. Alarmingly, the rapid growth of e-waste is outpacing formal waste collection and recycling systems by a factor of five (Baldé *et al.*, 2024), underscoring the urgent need for more effective e-waste management strategies. This explosive growth calls for a shift toward more sustainable production and consumption practices in the electronics industry.

Urgent Need for Effective E-Waste Management

The rapid increase in e-waste, coupled with the fact that only 22.3% is properly collected and recycled, raises serious concerns (Baldé *et al.*, 2024). Due to inadequate management systems, nearly 80% of e-waste bypasses formal processing channels and is instead handled through informal sectors. As e-waste generation continues to surge, the failure of infrastructure to manage its disposal has wide-ranging environmental, health, and economic consequences. Effective e-waste recycling not only holds immense economic potential but is crucial for minimizing risks to both the environment and public health.

When e-waste is poorly managed, it releases hazardous substances, such as 31 billion kilograms of metals, 17 billion kilograms of plastics, 58,000 kilograms of mercury, and 45 million kilograms of brominated flame retardants, into the environment (Baldé *et al.*, 2024). These

pollutants contaminate air, water, and soil, posing serious threats to workers and nearby communities. Inappropriate disposal methods, including incineration and chemical dissolution, emit toxins like dioxins, endangering human and animal health (Jain *et al.*, 2023). Moreover, burying e-waste allows toxic chemicals to leach into groundwater, undermining local ecosystems (Jain *et al.*, 2023). The external costs associated with improper handling of these hazardous substances, estimated at US\$78 billion, stem primarily from lead and mercury emissions, plastic leakages, and contributions to global warming (Baldé *et al.*, 2024)

Another concern is the transboundary movement of e-waste, which presents significant socio-environmental challenges. Although the Basel Convention was established to regulate the global transport of hazardous waste, including e-waste, and to prevent its export from affluent countries to less-developed regions, its non-binding nature weakens its effectiveness. In 2019 alone, approximately 5.1 Mt of e-waste were traded globally, with 3.3 Mt moving without proper oversight (Baldé *et al.*, 2022). Much of this unregulated waste is shipped from wealthier nations to lower-income areas, particularly in Africa and Southeast Asia, where safe disposal mechanisms are often inadequate. As a result, informal and unsafe recycling practices proliferate, amplifying environmental and public health risks in already vulnerable regions.

Despite these environmental and social challenges, e-waste also holds considerable economic benefits. Frequently termed an “urban mine”, it contains highly valuable materials such as gold, silver, copper, iron, zinc, and various rare metals. The total value of the 62 Mt of e-waste produced worldwide in 2022 is estimated at around US\$91 billion, of which around US\$28 billion was recovered through recycling efforts, most of which was metals, accounting for 31 Mt, including valuable metals such as gold, copper and zinc. This clearly demonstrates the

economic benefits of well-structured e-waste management and the potential opportunities available through improved technologies. The benefits of such e-waste management extend beyond materials recovery. Baldé *et al.* (2024) estimate that properly handling e-waste can yield a US\$23 billion reduction in greenhouse gas emissions by preventing the release of roughly 93 billion kilograms of CO₂-equivalent emissions

However, these gains were offset by substantial costs. Recycling treatments alone required an investment of US\$10 billion, while environmental and health damages from poorly managed e-waste were estimated at US\$78 billion, resulting in a net shortfall (Baldé *et al.*, 2024). These findings highlight both the substantial economic value of effective e-waste management and the severe repercussions of improper handling. The continued gap between e-waste generation and adequate disposal highlights the urgent need to improve recycling infrastructure and adopt strategies that fully realise the economic and environmental potential of better e-waste practices.

Circular Economy: Reducing E-waste generation and Enhancing E-waste Value

The Circular Economy (CE) approach provides a strategic framework for optimising value recovery from e-waste. In contrary to the traditional linear model, CE prioritises resource recovery, reuse, and regeneration, thereby substantially reducing waste generation and mitigating environmental harm. The application of CE principles to e-waste management can enhance resource efficiency, reduce environmental impacts, and unlock economic opportunities.

Product Recovery Management (PRM) is a key component of the CE, focusing on strategies that extend product lifecycles and enhance sustainability. Thierry *et al.* (1995) categorized value recovery into three main areas—waste management, product recovery management, and direct

use. While waste management primarily involves disposal through incineration and landfilling, PRM encompasses a spectrum of recovery options, such as repair, refurbishment, remanufacturing, cannibalization, and recycling, each offering varying degrees of value retention and resource efficiency. Repair involves minimal interventions to restore basic functionality; refurbishment provides moderate enhancements; remanufacturing restores or upgrades a product to near-new condition; cannibalisation extracts functional components for reuse; and recycling recovers raw materials, sacrificing the product's original form and function. These differentiated strategies collectively support a more sustainable and economically viable approach to end-of-life (EOL) product.

Remanufacturing: The Most Advanced Form of PRM

As the most advanced form of PRM, remanufacturing delivers significant economic, environmental, and energy-related advantages. By minimising reliance on virgin raw materials and reducing waste, remanufacturing has become a pivotal strategy in modern production systems and sustainability agendas.

Economically, remanufactured products are typically priced 30–40% lower than new products, offering cost-effective alternatives without compromising on quality (Giuntini and Gaudette, 2003). For businesses, remanufacturing can be highly profitable, with total costs significantly below those of manufacturing new products. Input costs for remanufactured goods are generally 40–50% of those for new items (Lee, Woo and Roh, 2017), and savings on certain core components can reach 40–60% (Chen and Chang, 2012). By reusing parts and components, companies not only reduce material costs and waste but also enhance profitability (Souza, 2013).

Industries reliant on heavy or material-intensive equipment especially benefit from remanufacturing, as it provides cost savings for large machinery (Fatimah and Biswas, 2016).

Remanufacturing significantly reduces both resource use and energy consumption. Studies show that it uses over 85% less energy than producing new products, resulting in substantial reductions in greenhouse gas emissions (Lee, Woo and Roh, 2017). The energy required in remanufacturing is far lower than in new manufacturing processes (Gutowski *et al.*, 2011), with remanufacturing machine tools alone saving over 80% of the energy compared to traditional manufacturing (Du and Li, 2014). Given these energy savings, remanufacturing stands out as a key strategy for achieving sustainable energy use (Fatimah and Biswas, 2016).

From an environmental perspective, remanufacturing is far more sustainable than traditional manufacturing, as it greatly reduces the need for raw materials, particularly those that are scarce or non-renewable. It is one of the most effective strategies for conserving energy and reducing emissions (Fatimah and Biswas, 2016). Compared to producing new products, remanufacturing saves both energy and material resources (Schau *et al.*, 2011). Most of the materials used in remanufactured products come from recycled sources, and the energy required for remanufacturing is far lower than that needed for producing new goods (Gutowski *et al.*, 2011).

Evolving Role of Remanufacturing in Sustainable Business Strategy

Historically, firms faced considerable obstacles in promoting remanufactured products, largely due to limited consumer awareness and resistance to paying for reprocessed goods perceived as inferior (Thierry *et al.*, 1995). However, environmental concerns and cost advantages have since elevated remanufacturing from a marginal activity to a core pillar of sustainable business

strategy. Today, it plays a critical role in advancing CE principles, supporting not only environmental objectives but also economic resilience and job creation (Zhang *et al.*, 2020).

Remanufacturing contributes to stabilising market prices and strengthening customer engagement through initiatives such as trade-in schemes and extended product lifecycle services—strategies that align with shifting consumer expectations and reinforce brand loyalty (European Remanufacturing Network, no date). As consumer demand grows for high-quality, cost-effective, and environmentally responsible products, remanufactured and refurbished goods offer a compelling value proposition: equivalent performance at reduced cost and with lower environmental impact.

For businesses, the integration of remanufacturing into core operations leads to tangible benefits, including reduced material input, lower operational costs, and enhanced resource efficiency. These outcomes not only improve environmental performance but also support long-term competitiveness by increasing supply chain resilience and meeting corporate social responsibility (CSR) targets. Consequently, PRM and remanufacturing are no longer ancillary functions but essential components of forward-looking, sustainable business models.

Expanding the Size of Market for Remanufactured Products

The remanufactured products market is expanding rapidly, driven by the economic and environmental benefits of remanufactured products, as well as the economic and social responsibility advantages for companies. The estimated size of the global remanufactured electronics market varies significantly across different reports, ranging from US\$ 50 billion to US\$ 270 billion in 2024. Despite these variations, projections consistently indicate strong

growth at a compound annual growth rate (CAGR) exceeding 10% (Business Research Insights, 2024; Consegic Business Intelligence, 2024; Credence Research, 2024b; KD Market Insights, 2024; Spherical Insights, 2024a; Coherent Market Insights, 2025).

Among remanufactured product categories, smartphones and PCs constitute the largest segments in terms of market size and growth potential. The remanufactured smartphone market is projected to reach approximately US\$ 80 billion in 2024 and, with a CAGR of around 12%, is expected to exceed US\$ 250 billion by 2034 (Credence Research, 2024c; Future Market Insights, 2024; Spherical Insights, 2024c). Although smaller than the smartphone segment, the remanufactured PC market is also experiencing steady growth. Industry reports estimate its market size at around US\$ 11 billion in 2024, with projections indicating an increase to around US\$ 20 billion by 2032 at a CAGR of about 6%, despite variations in estimates across different sources (Credence Research, 2024a; Spherical Insights, 2024b; Valuates Reports, 2024).

Evolution of Remanufacturing Research: Consumer-Centric Insights

As consumer and corporate interest in remanufacturing has grown, the market expansion has been accompanied by an increasing body of research in this field. Over time, research on remanufacturing has evolved significantly, shifting from a primarily operational focus to more complex empirical and consumer behaviour studies. Early research in the remanufacturing domain primarily centred on remanufacturing processes optimisation, system efficiency, and return forecasting, often relying on assumptions such as the unlimited availability of used products and fixed acquisition costs (Van der Laan and Salomon, 1997; Galbreth and Blackburn, 2006, 2010; Liang, Jin and Ni, 2014; Chen *et al.*, 2015; Aydin *et al.*, 2018). However, the limitations of these theoretical models soon became evident, prompting calls for empirical

validation to better account for the complexities inherent in real-world applications (Atasu, Guide and Van Wassenhove, 2008; Guide and Van Wassenhove, 2006, 2009).

Responding to these calls, recent research has increasingly turned towards empirical investigations, particularly into consumer behaviour and market dynamics surrounding remanufactured products. This shift has expanded the analytical focus to include factors such as consumer willingness to pay (WTP), perceived value and price differentials between new and remanufactured products. Empirical studies typically fall into two broad approaches: primary research, which utilises surveys and interviews to capture consumer perceptions, preferences, and purchase intention; and secondary research, which leverages transactional data from online platforms such as eBay to examine actual purchasing patterns and market behaviour.

Primary research has identified several key factors influencing consumer decisions regarding remanufactured products. These include product knowledge, perceived risks, environmental and quality concern and ambiguity tolerance (Hazen *et al.*, 2012; Abbey *et al.*, 2015; Wang and Hazen, 2016; Abbey *et al.*, 2017; Sun, Teh and Linton, 2018; Zhou, Xiong and Jin, 2021; Shevchenko *et al.*, 2023). However, a notable challenge in remanufacturing research is the discrepancy between consumers' expressed environmental concerns and their actual purchasing behaviour. Khor and Hazen (2017) found that while consumers originally intended to purchase remanufactured products, they are more likely to buy energy-efficient or new products instead. Wang and Kuah (2018) similarly observed that even environmentally conscious consumers may hesitate to purchase remanufactured goods, pointing to a gap between attitude and actual action.

To explore real-world consumer behaviour toward remanufactured goods in digital marketplaces, recent studies have increasingly utilised secondary transaction data from platforms such as eBay. By analysing actual transaction records, prior research has identified key drivers of price differentials between new and remanufactured products (e.g., Subramanian and Subramanyam, 2012; Pang *et al.*, 2015; Zhou and Gupta, 2019), as well as market features influencing variations in consumer WTP across new, remanufactured, and used conditions (Frota Neto, Bloemhof and Corbett, 2016). These studies predominantly rely on traditional econometric linear regression (LR) models, while interpretable but limited in their ability to capture complex interactions and non-linear effects. Extending this line of inquiry, subsequent research has examined consumer valuation and WTP of remanufactured goods in auction settings, where prices are dynamically determined (e.g., Xu, Zeng and He, 2017; Casalin and Dia, 2019). These works investigate the impact of various factors and market signals on final auction prices, offering insights into consumer perceptions and bidding strategies, but similarly remain constrained by their reliance on LR frameworks.

Unlike previous studies relying on LR methods, Van Nguyen *et al.* (2020) applied machine learning (ML) techniques to predict demand for remanufactured products, incorporating a broad set of buyer and seller signals. Their findings highlight the limitations of traditional LR models in capturing the complex, non-linear patterns that shape consumer behaviour in online markets for remanufactured goods and demonstrate that ML methods yield improved predictive performance by identifying latent structures and complex interactions among market signals.

Research Gaps

Despite growing interest in remanufactured products as enablers of sustainable consumption and CE practices, critical research gaps remain, particularly in the context of online auction settings, where pricing dynamics and consumer behaviour are underexamined.

First, research on market signals in online auctions for remanufactured products remains significantly underdeveloped compared to fixed-price settings. While early studies in fixed-price contexts incorporated various features including market signals as key price factors (Subramanian and Subramanyam, 2012; Pang *et al.*, 2015; Frota Neto, Bloemhof and Corbett, 2016; Zhou and Gupta, 2019), and similar approaches are later extended to auctions (Xu, Zeng and He, 2017; Casalin and Dia, 2019), these studies have primarily relied on LR models. More recently, Van Nguyen *et al.* (2020) advanced the field by demonstrating that ML models outperform traditional LR methods in predicting demand using seller- and user-generated signals on fixed-price platforms. However, auction markets have yet to receive equivalent attention—auction-specific and platform-level signals remain largely unexplored, and to date, no study has applied ML techniques for pricing or demand prediction in auction contexts.

Secondly, prior research has largely failed to account for the impact of detailed condition levels within remanufactured products. Most studies have treated remanufactured goods as a homogeneous category, whether comparing them to new products (e.g., Subramanian and Subramanyam, 2012; Pang *et al.*, 2015) or to items of varying conditions (Frota Neto, Bloemhof and Corbett, 2016; Xu, Zeng and He, 2017; McKie *et al.*, 2018; Silva *et al.*, 2018). In contrast, research on used goods has examined the role of specific condition levels in shaping product valuation (Kwak, Kim and Thurston, 2012; Makov *et al.*, 2019). In practice, remanufactured

products span a wide range of conditions; for example, eBay classifies remanufactured products into categories such as Certified, Excellent, Very Good, Good, and Seller Refurbished. Despite detailed condition distinctions, research has rarely examined their impact on customer behaviour or WTP, leaving a key gap in understanding remanufactured product markets.

Third, bidder heterogeneity in auctions involving remanufactured products remains significantly under-explored. Existing research has predominantly concentrated on WTP and pricing mechanisms, whether in fixed-price or auction formats, while offering limited insight into the differentiated bidding behaviours that emerge in response to remanufactured goods. While studies on bidder heterogeneity using clustering techniques have provided useful insights into general bidding dynamics (Bapna *et al.*, 2004, 2009; Goes, Karuga and Tripathi, 2012; Chang, 2014; Lu *et al.*, 2016), they have rarely been applied in the context of remanufactured product auctions. This is a critical oversight, as consumers often perceive such products with scepticism due to concerns regarding quality, reliability, and warranty conditions. As a result, the limited attention to bidder heterogeneity constrains a fuller understanding of consumer decision-making under heightened uncertainty and information asymmetry.

In summary, although remanufactured products are gaining prominence within sustainability and CE agendas, substantial gaps remain in understanding their dynamics within auction-based marketplaces. Key limitations include a lack of research on auction-specific signalling mechanisms, insufficient consideration of product condition heterogeneity, and limited insights into how bidders behave under uncertainty. Moreover, while ML techniques have been increasingly applied, their limited interpretability constrains their utility for theoretical advancement and practical decision-making.

1.2 Motivation

The accelerating shift toward sustainability has elevated the role of remanufactured products in global markets. Online auction platforms, particularly eBay, have become central to their distribution. While the environmental and economic benefits of remanufacturing are well established, the mechanisms driving price formation and market behaviour within auction-based settings are insufficiently understood.

First, online auctions present a fundamentally distinct transactional environment, characterised by real-time competition, time pressure, and heightened quality uncertainty, which amplifies information asymmetry and likely alters how consumers perceive and react to market signals. While prior research has thoroughly investigated market signals in fixed-price contexts (e.g., Subramanian and Subramanyam, 2012; Frota Neto, Bloemhof and Corbett, 2016; Zhou and Gupta, 2019; Van Nguyen *et al.*, 2020), significantly less attention has been given to auction-specific and platform-level signals remain underexplored involving remanufactured products (e.g., Xu, Zeng and He, 2017; Casalin and Dia, 2019; Zhou and Gupta, 2019). Notably, given that sellers are more likely to choose auction formats over fixed pricing when dealing with used or remanufactured goods (Chen, Lai and Yu, 2018), further underscoring the need to better understand this market context.

Second, as remanufactured products gain wider adoption through platforms like eBay and Amazon Renewed, accounting for condition-level differences has become increasingly important. These products are now categorised in detail, such as Certified, Excellent, or Seller Refurbished, yet most prior studies treat remanufactured goods as a uniform category when compared to new items (Subramanian and Subramanyam, 2012; Pang *et al.*, 2015) or other

conditions (Frota Neto, Bloemhof and Corbett, 2016; Xu, Zeng and He, 2017; McKie *et al.*, 2018; Silva *et al.*, 2018). While used-product research has more thoroughly explored condition-specific effects (Kwak, Kim and Thurston, 2012; Makov *et al.*, 2019), remanufacturing studies have yet to do so. As such, there is a clear need to investigate how condition granularity affects consumer behaviour and valuation.

Third, bidder heterogeneity in remanufactured product auctions has received limited attention, despite its importance for understanding auction dynamics in this context. Existing auction research primarily focuses on new products and fails to capture the behavioural complexities associated with remanufactured goods, such as heightened information asymmetry and quality concern. These factors significantly influence how bidders assess value, interpret signals, and manage risk. Although heterogeneity has been explored in general auction settings, little is known about how such conditions shape bidding strategies for remanufactured products. This gap limits the explanatory power of current models and highlights the need for context-sensitive frameworks that reflect the behavioural nuances of this market. Furthermore, given that auction formats are often preferred by sellers of remanufactured goods (Chen, Lai and Yu, 2018), advancing the understanding of bidder behaviour in these settings is both timely and essential.

The last motivation lies in the limitations of existing studies that employ ML techniques. Van Nguyen *et al.* (2020) utilised auxiliary interpretability tools, such as variable importance ranking and partial dependence plots, to mitigate the black-box nature of ML models in predicting demand for remanufactured products. However, these simple post-hoc explanations remain limited in both their depth (focusing primarily on global interpretation) and transparency, highlighting the need for more robust and integrated approaches. Likewise, clustering

approaches used in prior studies (e.g., Bapna *et al.*, 2004, 2009) often lack transparency, as the defining characteristics of each segment remain unclear. To overcome these challenges, this study adopts explainable artificial intelligence (XAI) techniques, specifically SHAP (SHapley Additive exPlanations), to enhance the explainability of both predictive and clustering models. By embedding explanation-based features into the analytical framework, the study improves transparency and enables a clearer understanding of how different variables drive auction outcomes and segment differentiation.

Taken together, these gaps highlight the urgent need for a more comprehensive and interpretable analytical framework to understand auction behaviour in remanufactured product markets. This study addresses this need by combining ML techniques with XAI methods to examine how platform-level signals, condition granularity, and bidder heterogeneity jointly influence auction outcomes.

1.3 Research Objectives and Research Questions

This study aims to address the identified research gaps by empirically investigating the dynamics of online auctions for remanufactured electronic products through the application of data mining, ML, and XAI techniques. By focusing on an auction environment characterised by high information asymmetry and quality uncertainty, the research seeks to contribute both theoretically and practically to a deeper understanding of this underexplored market. Ultimately, the goal is to generate insights that support the development of more efficient, transparent, and sustainable online marketplaces for remanufactured goods. To this end, the study is guided by three core research objectives:

Objective 1: To enhance understanding of the market signals that influence auction prices in remanufactured product auctions, where information asymmetry is high.

The first objective of this study is to investigate the impact of market signals on auction final prices, for remanufactured electronic products. In online auctions for remanufactured goods, where information asymmetry is inherent and quality concern is high, signals such as seller reputation, product descriptions, and pictures are critical in reducing uncertainty and influencing buyer behaviour. Van Nguyen *et al.* (2020) demonstrated the effectiveness of ML in capturing the non-linear effects of such signals on demand prediction. Extending this work, this study incorporates platform-level signals, such as historical sales volume and concurrent listings, to provide a more comprehensive analysis. By jointly modelling seller-, buyer-, and platform-side signals, the research aims to capture their interactive effects on auction performance. To enhance both predictive accuracy and interpretability, the study applies SHAP, an XAI method. This approach enables a transparent decomposition of model predictions, offering deeper insight into how each market signal contributes to auction price formation.

Objective 2: To examine how varying condition levels of remanufactured products influence auction prices and the effects of market signals.

The second objective of this study is to investigate how detailed condition classifications within the remanufactured product category, such as Certified, Excellent, Very Good, Good, and Seller Refurbished, affect final auction prices and the importance and dynamics of market signals. Existing studies often treat remanufactured products as a uniform category, overlooking the behavioural impact of condition-specific distinctions. However, platforms like eBay actively use such distinctions to shape consumer expectations and guide seller positioning, suggesting these labels may have substantial implications for buyer valuation and market dynamics. This

study addresses this gap by split the remanufactured product by condition and empirically examining how different condition levels influence auction outcomes and market signal dynamics. By analysing variations of auction price and market signals across these subcategories, the research offers a deeper understanding of how remanufactured products are perceived, priced, and presented in online auction environments.

Objective 3: To explore bidder heterogeneity in remanufactured product auctions

This objective seeks to investigate the heterogeneity of bidder behaviour in remanufactured product auctions, a factor that remains insufficiently studied despite its relevance to auction performance. Drawing on transaction-level data from remanufactured smartphone auctions, the study applies clustering techniques to identify distinct bidder segments. To improve interpretability, the analysis integrates an explainable clustering framework by reframing the clustering task as supervised classification. Cluster labels are treated as target variables, with SHAP used to determine the key features that distinguish each segment. This approach enables a transparent understanding of the behavioural drivers underlying bidder segmentation and allows the study to link bidder types to auction success rates and profitability outcomes.

To achieve the objectives, a diverse sample of remanufactured electronic products is collected from eBay to examine the factors influencing final auction prices. In parallel, data on bidder behaviour and associated features are compiled to enable a comprehensive analysis. The study employs a combination of analytical approaches, including statistical LR models and ML techniques for regression, classification, and clustering tasks. Against this methodological backdrop, the thesis addresses the following research questions:

- 1. How do market signals from sellers, buyers, and the platform influence final auction prices for remanufactured electronics?**
- 2. How do auction prices and effects of market signals vary by the condition level of remanufactured products?**
- 3. What bidding strategies do bidders adopt in remanufactured product auctions?**

By addressing these research questions, the thesis aims to bridge critical gaps in the literature related to information asymmetry, product condition variability, and bidder heterogeneity in the remanufactured product market, ultimately contributing to more effective auction strategies and enhanced market transparency.

1.4 Outline

The structure of this thesis is as follows. Chapter 2 presents a comprehensive review of the relevant literature, situating the study within the context of existing research. Chapter 3 outlines the methodological framework developed to achieve the research objectives. Chapter 4 examines the market signals generated by buyers, sellers, and the online platform, and investigates how these signals influence the final auction prices of remanufactured electronics. Chapter 5 explores how price-determining factors vary according to the condition of remanufactured products, providing deeper insights into seller behaviour and pricing strategies. Chapter 6 addresses bidder heterogeneity by utilising explainable clustering techniques to categorise and analyse the diverse bidding strategies observed in remanufactured product auctions. Finally, Chapter 7 synthesises the empirical findings, highlights the key contributions of the study, and outlines directions for future research.

Chapter 2

Literature Review

2.1 Introduction

Building on the research gap, objectives, and questions identified in Chapter 1, this chapter reviews the relevant literature on the online market for remanufactured products, with a focus on online auction environments. It critically examines key research areas such as information asymmetry, signalling, consumer behaviour and WTP for remanufactured goods, bidding strategies, and the use of AI methods. Through critical analysis of existing studies, the chapter establishes a conceptual and empirical foundation for understanding the market dynamics and behavioural patterns that shape the exchange of remanufactured goods in digital marketplaces.

This chapter is structured as follows. Section 2.2 reviews empirical research on consumer behaviour towards remanufactured products, with particular attention to studies utilising real transaction data. Section 2.3 explores research on the classification of various product conditions, and their influence on consumer perceptions and pricing outcomes. Section 2.4 discusses clustering bidding strategies in online auction, covering bidder heterogeneity, difference by experience, and the application of explainable clustering approaches. Section 2.5 presents key economic theories of information asymmetry and signalling, emphasising their role in reducing adverse selection in online and remanufactured product markets.

2.2 Empirical Research on Consumer Behaviour Toward Remanufactured Products

The growing need for empirical research on consumer behaviour toward remanufactured products has led to an increasing reliance on real transaction data. While primary data models effectively capture consumer perceptions, they often fail to reflect actual purchasing behaviour (e.g., Khor and Hazen, 2017; Wang and Kuah, 2018). To bridge this gap, recent studies have increasingly adopted real-world transaction data, employing LR analysis and, more recently, ML techniques to more accurately examine market dynamics, price determinants, and the role of market signals in remanufactured goods markets.

The foundation for empirical research on remanufactured products was laid by Guide and Li (2010), who examined field experiments using online auctions of consumer product (Skil Jigsaw) and commercial product (Cisco Security System) on eBay to examine the potential cannibalization of new product sales by remanufactured products in closed-loop supply chains (CLSCs). Their analysis, based on nonparametric statistical tests, revealed minimal cannibalization in consumer markets, while commercial markets exhibited greater overlap between bidders, indicating a higher risk of cannibalization.

Expanding on this, Subramanian and Subramanyam (2012) empirically examined key factors influencing price differentials between new and remanufactured electronics sold on eBay. Using transaction data, the authors found that seller reputation and remanufacturer identity significantly influenced consumer WTP for remanufactured products. Specifically, products remanufactured by original equipment manufacturers (OEMs), or their authorised facilities attracted higher prices compared to third-party remanufacturers. Conversely, warranty strength

did not significantly impact price differentials when reputation signals were already present. These findings suggest that seller reputation and OEM association are critical determinants in consumer decision-making, affecting the market viability of remanufactured products.

Similarly, Pang *et al.* (2015) examined factors determining price differentials between new and remanufactured electronics sold on eBay UK using both fixed and non-fixed price listings from 1,260 new and 917 remanufactured electronics. Through a log-normal OLS model with Ridge and Mixed Regression, they identified seller reputation, warranty length, demand and supply proxies, listing duration and listing end time, and return policies as significant determinants of price differentials. Their findings highlighted that seller identity significantly influenced prices, with non-manufacturer-approved vendors experiencing wider price differentials. Additionally, longer warranties, higher seller reputation, and favourable return policies effectively reduce price differentials, increasing consumer WTP for remanufactured goods.

Moving beyond price differentials, Frota Neto, Bloemhof and Corbett (2016) examined consumer perceptions of remanufactured products relative to new and used products, using data from 1,716 iPod transactions on eBay. They explored quality signals provided by sellers—textual descriptions (positive keywords included) and visual cues (number of product pictures)—to assess their impact on consumer WTP. Their results revealed that textual quality cues significantly increased prices for used products but had little or no effect on remanufactured and new products. However, visual cues showed mixed and inconclusive results. Their findings contribute to the literature by empirically demonstrating that the effectiveness of quality signals varies across product condition levels, particularly in reducing consumer uncertainty associated with information asymmetry in online marketplaces.

Shifting focus to e-services, Xu, Zeng and He (2017) explored the impact of e-services on WTP for remanufactured products in online auctions and fixed-price transactions. Using data from 3,002 auctions and 1,657 fixed-price sales of Apple iPad 2 products sold on eBay, they found that e-service offerings during the information phase had the strongest positive impact on consumer WTP in both transaction types. Additionally, all four phases of e-service offerings—Information, Agreement, Fulfilment, and After-sales—significantly influenced consumer WTP in auction transactions but had less influence in fixed-price transactions. The results indicate that consumers in auction environment are more reliant on e-service offerings due to greater uncertainty and perceived risk associated with auction transactions.

McKie *et al.* (2018) conducted an empirical study on consumer decision-making, examining how factors such as price, product generations (e.g., iPad 1 to 4), condition types (e.g., New, New-Open Box, Manufacturer Refurbished, Seller Refurbished, Used), seller characteristics (e.g., reputation, communication score), and various listing attributes influence purchasing behaviour. To analyse consumer choices, they employed structural estimation models from the industrial organisation literature, specifically using a multinomial logit discrete-choice model framework. Their findings highlighted that product generation and condition significantly influenced consumer purchase decisions. Notably, refurbished products were found to compete closely with new products, posing a similar level of cannibalisation threat as used products.

Casalin and Dia (2019) investigated how information and reputation mechanisms influence auction outcomes for remanufactured electronic products on eBay, specifically addressing the issue of asymmetric information. Analysing a dataset comprising 920 auctions in 20 electronics

categories, they explored several reputation mechanisms, including seller feedback scores, return policies, and certifications by manufacturer-approved vendors, and their effectiveness in reducing consumer uncertainty. They found that these mechanisms act either as substitutes or complements, depending on the value of the auctioned items. Seller reputation scores significantly influenced buyer behaviour for lower-value transactions, whereas return policies and manufacturer certifications were more impactful for higher-value items.

Zhou and Gupta (2019) examined pricing strategies for new and remanufactured high-tech products across multiple product generations, specifically using 800 Apple iPhones. Analysing transaction data collected from eBay, they identified key factors influencing the pricing of both new and remanufactured products, including product generation, perceived quality, storage capacity, market positioning, innovation level, seller reputation, warranty offerings, and transactional factors such as sales volume and customer reviews. They highlighted two main depreciation trends influencing prices: technological depreciation (linked to product generation and age) and quality depreciation (associated with remanufacturing condition).

Zhou and Gupta (2020) further investigated factors influencing value depreciation of new and remanufactured high-technology products, specifically Apple iPhones and iPads, using transactional data from eBay and customer attention data from online platforms. The authors applied partial least squares (PLS) regression to identify key factors influencing the depreciation rate, categorised as marketing elements (e.g., time since product release), technological features (e.g., camera resolution, operating system upgradeability, chipset memory), design attributes (e.g., product thickness, weight, screen size), and customer attention metrics (e.g., hits, fans-to-hits ratio). Their findings showed that time since release, product

thickness, camera resolution, and fans/hits ratio significantly influenced depreciation rates for both iPhones and iPads, while features like ApplePay slowed depreciation for iPhones, and cellular data functionality increased depreciation for iPads.

Van Nguyen *et al.* (2020) developed a data mining and ML approach to accurately predict customer demand for remanufactured products using real-world transaction data from Amazon. Employing tree-based regression methods such as Classification and Regression Tree (CART), M5, and Random Forest models, they demonstrated that ML techniques significantly improved predictive accuracy compared to traditional LR models. They identified key online market signals, including overall product ratings, sentiment of customer reviews, answered questions, warranty disclosure, textual descriptions, and visual cues, that influenced customer demand. Furthermore, the study utilised variable importance rankings and partial dependence plots to interpret complex, non-linear relationships between market signals and consumer demand, providing actionable managerial insights for marketing remanufactured products.

Table 2.1 summarises prior studies on customer behaviour toward remanufactured products, detailing the dependent and independent variables used, the sales formats examined, and the analytical models applied. Most studies focused on fixed-price formats, with only four addressing auctions. Guide and Li (2010) analysed bidding data to assess WTP and potential cannibalisation of new product sales. Pang *et al.* (2015) included auction prices among various sales formats to study price differentials. Xu, Zeng and He (2017) and Casalin and Dia (2019) examined multiple auction-related variables, but unlike Van Nguyen *et al.* (2020), did not explore non-linear relationships or feature interactions using ML. This highlights a methodological gap in the literature on remanufactured product auctions.

Table 2.1. Summary of Literature on Customer Behaviour Towards Remanufactured Products

Article	Variable Description		Buying Format		Analysis Model		
	Dependent	Independent	Auction	Fixed price	Linear	ML	Interaction
Guide & Li (2010)	WTP (New & Reman.)	Bidder ID, Bid Amount, Time of Bid	✓		✓		
Subramanian & Subramanyam (2012)	Price Differential (New & Reman.)	Seller Reputation (Positive & Negative), Seller Incumbency, OEM Authorised, Authorised Seller, Warranty Strength, Quantity Available, Demand Proxy, Selling Fee, Listing Time (Weekend & Night)		✓	✓		
Pang, Casalin, Papagiannidis, Muyldermans & Tse (2015)	Price Differential (New & Reman.)	Seller Reputation (Positive & Negative), Seller Incumbency, Seller Identity (Authorised), Warranty Length, Return Policy , Demand & Supply Proxy, Listing Duration, Listing Time (Time & Day)	✓	✓	✓		
Frota Neto, Bloemhof & Corbett (2016)	Selling Prices (New, Reman. & Used)	Product Conditions, Positive Keywords, Original Pictures, Feedback (Positive & Negative), Memory, Generation, Shipping Cost		✓	✓		
Xu, Zeng & He (2017)	WTP (New, Seller Reman., Manufacturer Reman. & Used)	Production Conditions, Number of Pictures, Service Failure, Seller Tenure, Return, Bid Count, Autopay, Expedited Shipping,	✓	✓	✓		
McKie, Ferguson, Galbreth & Venkataraman (2018)	Consumer Choice	Condition, Generation and Storage Size, Price and Shipping Fees, Return Policy and Warranty Length (Return Policy, Restock Fee, Re-ship, Warranty Length), Listing Time Details (Month, Total Active), Seller Reputation (Feedback Score, Net Feedback Score, Net Negative, Net Positive, Item Description Score, Shiptime Score, Communication Score, Shiphand score, Seller Incumbency), Other controls		✓	✓		
Casalin & Dia (2019)	Selling Price (Reman.)	Reputation (Positive & Negative), Seller Incumbency, Seller Identity (Manufacturer-Approved), Warranty, Return Policies, Auction Duration, Listing End Time and Date	✓		✓		
Zhou & Gupta (2019)	Selling Price (New), Price Differential (New & Reman.)	Stars level, Percentage of Positive Feedback, Warranty Length and Cost, Transaction Quantity, Number of Reviewers, Condition, Product Generation, Storage Level, Product Level, Innovation Level		✓	✓		

Zhou & Gupta (2020)	Value Depreciation Rate, Price Difference (New & Reman.)	Condition, Hit Increase, Fans/hits ratio, Hits trend, Fans/hits ratio trend, Time Since Release, Market Positioning, Storage Capacity, Thickness, Weight, Resolution, Screen Size, OS Upgradable, Chipset Memory, Camera, ApplePay, Battery, Design, Feature, Performance, Market Status, Fold or Unfold		✓	✓		
Van Nguyen, Zhou, Chong, Li & Pu (2020)	Sales Rank	Overall Rating, Feedback (Positive & Negative), Review Volume, Review Sentiments, Number of Helpfulness Votes, Number of Answered Questions, Product Description, Pictures, Discount Rate, Stock Availability, Warranty Information, Price Difference		✓	✓	✓	✓

2.3 Impact of Product Condition on Market Value and Consumer Perception

As discussed in the previous section, product condition is a critical factor in determining the market value of remanufactured products. In both the used and remanufactured markets, consumer concerns regarding perceived risk and product quality play a significant role in shaping purchasing decisions. Existing research on this topic can be broadly categorised into:

- **Comparison Between New and Remanufactured Products:** This stream investigates factors such as seller reputation, warranty availability, and quality signals that influence the price differential and consumer WTP between new and remanufactured products.
- **Comparison Across Broad Condition Categories:** The second stream explores a broader range of product condition types (e.g., New, Remanufactured, Used) examine their impact on selling price in online marketplaces.
- **Comparison of Detailed Product Conditions Levels:** The third stream focuses on more detailed condition gradations (e.g., Excellent, Very Good, Good) and analyses their effects on buyer perceptions, and resale value.

2.3.1 Comparison Between New and Remanufactured Products

Empirical research comparing consumer WTP for new versus remanufactured products has primarily focused on price differentials, consumer perception, and market dynamics. Guide and Li (2010) conducted auction-based experiments to examine cannibalisation effects, revealing that WTP differs significantly between new and remanufactured products, with minimal bidder overlap in consumer electronics. Expanding on this, Subramanian and Subramanyam (2012)

examined eBay transaction data to identify the drivers behind price differentials, while Pang *et al.* (2015) investigated similar dynamics using eBay UK data, focusing on the electronics sector.

Studies have also explored consumer behaviour and product depreciation patterns. Zhou and Gupta (2019) examined high-tech products like iPhones and iPads, finding that while new products depreciate rapidly due to continuous technological advancements, remanufactured products follow a different depreciation trajectory, influenced by residual quality and retained technological features. Zhou and Gupta (2020) extended this analysis using eBay sales data and a PLS approach, identifying key depreciation factors such as time since release, product thickness, and camera resolution. Their study highlighted that while remanufactured products are often perceived as lower in quality, pricing reflects both technological and aesthetic considerations, underscoring the complexity of pricing strategies in the remanufacturing sector.

Further complementing this, Chen, Wang and Jia (2020) conducted an experimental study on consumer preferences for new, refurbished, and remanufactured products. Their findings indicate that even minor variations in product condition significantly impact WTP and purchasing decisions. While new products remain the preferred choice due to brand appeal and quality assurance, the specific condition of remanufactured products is critical in shaping consumer price acceptance.

2.3.2 Comparison Across Broad Product Condition Categories

Extending beyond the conventional comparison between new and remanufactured products, recent research has examined a wider spectrum of product conditions, such as new, used, seller-remanufactured, and manufacturer-certified remanufactured items, and their impact on

consumer behaviour, pricing strategies, and seller positioning in online marketplaces. By examining these variations, researchers provide a more nuanced understanding of how different product conditions affect market dynamics and purchasing decisions.

Studies on price positioning across different product conditions have shown that remanufactured products consistently sell at a discount compared to new products. Frota Neto, Bloemhof and Corbett (2016) confirmed that remanufactured products were sold at a discount relative to new products but commanded a significant price premium over used products, indicating higher perceived quality. Their findings suggest that rigorous remanufacturing processes help reduce consumer uncertainty, making remanufactured products a more attractive alternative to used goods while still being more affordable than new items.

Further research on pricing structures has examined how consumers perceive and evaluate different product conditions in online marketplaces. Xu, Zeng and He (2017) analysed WTP across multiple product conditions, including new, manufacturer-remanufactured, seller-remanufactured, and used products, in both auction and fixed-price formats. Their findings indicate that seller-remanufactured products attract a higher price than used goods, while manufacturer-certified remanufactured and new products command even greater WTP.

Building on these, McKie *et al.* (2018) examined consumer preferences across multiple product generations and conditions, including new, open-box, manufacturer-refurbished, seller-refurbished, and used products. Their study found that manufacturer-remanufactured products are perceived as closer substitutes to new items than seller-refurbished alternatives, reinforcing the importance of certification in influencing consumer trust. The study also highlighted that

remanufactured products pose a competitive risk to new products, similar to used goods, with consumer preferences dependent on product generation, condition, and seller reputation.

While much of the existing research has focused on consumer purchasing behaviour, other studies have examined how sellers adapt their strategies based on product condition. Silva *et al.* (2018) shifted the focus toward seller success factors in online marketplaces, analysing sales data to determine what drives transaction volume. Their findings challenge the assumption that product condition alone significantly influences sales volume, showing that seller-related factors such as auction volume, pricing strategy, and inventory variety are often more critical in determining actual sales performance.

Further research on seller strategies has explored how sellers adjust their listing formats to maximize sales. Chen, Lai and Yu (2018) found that sellers strategically select listing formats to manage valuation uncertainty and attract buyers. Their study shows that used and refurbished products, which experience greater price variability, are more frequently sold through regular auctions or Buy-it-Now (BIN) auctions, while fixed-price listings are less commonly used for these product conditions. In contrast, new products, which have more predictable market values, are predominantly sold through fixed-price listings, as pricing is more stable and widely accepted. These findings suggest that sellers carefully adapt their listing formats based on product condition to balance pricing flexibility and buyer confidence.

Casalin and Dia (2019) further reinforced the importance of product condition in online auctions for remanufactured products. Their research demonstrates that manufacturer-certified remanufactured items benefit from higher perceived quality, making formal assurances such as

certifications and return policies crucial for higher-value products. Conversely, lower-value remanufactured goods rely more on seller reputation indicators, such as feedback scores, to build trust and secure sales. The results highlight the role of certification in reducing consumer uncertainty while also emphasizing the significance of seller reputation in transactions involving lower-value remanufactured products.

2.3.3 Comparison of Detailed Product Condition Levels

While much of the literature on remanufactured value centres on broad comparisons between new, used, and remanufactured products, or general patterns of depreciation, a critical gap remains in the analysis of condition-specific categories within remanufactured goods. Remanufactured products are not uniform in quality—they are often graded into tiers such as Excellent, Very Good and Good—yet these finer distinctions have received limited scholarly attention. A few studies adopt a more granular lens, using detailed quality assessments to classify products across condition levels like excellent, fair, or poor. These approaches offer deeper insights into how subtle differences in product condition affect resale value and influence consumer purchasing behaviour.

Research has shown that both cosmetic appearance and functional performance significantly influence resale value in the secondary market. Kwak, Kim and Thurston (2012) categorized cosmetic conditions into four levels—Poor, Fair, Good and Excellent—and demonstrated that while a product’s visual appeal influences pricing, operational performance plays an equally vital role. Their findings suggest that maintaining superior cosmetic quality maximizes market value, while ensuring functional integrity enhances resale potential, reinforcing the need for both aesthetic and technical refurbishment in the remanufactured product sector.

Building on these insights, Makov *et al.* (2019) investigated how cosmetic condition impacts smartphone resale prices. Using a three-point grading scale—Excellent, Moderate, and Bad, they found that devices in excellent physical condition consistently command significantly higher prices than those in poor condition. While other factors such as repairability and memory capacity contribute to overall product value, their study confirmed that cosmetic appearance exerts the strongest influence on consumer purchasing decisions in the second-hand market.

Table 2.2 presents a structured summary of prior research that compares remanufactured products with other condition categories (e.g., new, used, manufacturer-remanufactured, seller-remanufactured) or investigates condition variation within a single category of used goods. While these studies provide important insights into how product condition affects consumer perception, value assessment, and market behaviour, a significant gap remains: little empirical attention has been given to the condition gradations within remanufactured products.

Table 2.2: Summary of Literature Examining Various Product Conditions

Article	Transaction		Comparing Product Condition					Remarks
	Auction	Fixed Price	New	Manufacturer-Remanufactured	Seller-Remanufactured	Refurbished	Used	
Comparison between New and Remanufactured								
Guide & Li (2010)	✓		✓	✓				Examines potential cannibalization effects
Subramanian & Subramanyam (2012)		✓	✓	✓				Identifies key drivers of price differentials
Pang, Casalin, Papagiannidis, Muyldermans & Tse (2015)	✓	✓	✓	✓				Investigates factors influencing price differentials
Zhou & Gupta (2019)		✓	✓	✓				Analyses price depreciation patterns
Zhou & Gupta (2020)		✓	✓	✓				Identifies product features influencing depreciation rates and pricing differences between
Chen, Wang & Jia (2020)		✓	✓	✓			✓	Evaluates consumer sensitivity to detailed condition descriptions
Comparison across Broad Product Conditions								
Frota Neto, Bloemhof & Corbett (2016)		✓	✓	✓			✓	Establishes market price new, remanufactured, used products
Xu, Zeng & He (2017)	✓		✓	✓	✓		✓	Assesses how e-service quality impacts consumer online purchasing behaviour
Chen, Lai & Yu (2018)		✓	✓			✓	✓	Investigates the impact of product condition on sellers' listing strategies and consumer purchasing decisions

McKie, Ferguson, Galbreth & Venkataraman (2018)		✓	✓	✓	✓	✓		Explores consumer preferences and evaluations
Silva, Moro, Rita & Cortez (2018)		✓	✓		✓	✓		Examines seller-related factors as primary determinants of smartphone sales,
Casalin & Dia (2019)	✓		✓	✓	✓			Examines how information and reputation affect buyer trust and price formation
Detailed Conditions Levels								
Kwak, Kim & Thurston (2012)		✓					✓ (Detailed)	Analyses second-hand product value
Makov, Fishman, Chertow & Blass (2019)		✓					✓ (Detailed)	Investigates smartphone resale value

2.4 Bidding Strategies in Online Auction

Bidding behaviour in online auctions is highly diverse, shaped by bidder characteristics, auction design, and accumulated experience. Earlier research moved beyond classical assumptions of rational, uniform bidders, identifying distinct strategic types, such as Evaluators, Opportunists and Snipers, through clustering methods based on bid timing, frequency, and behavioural traits. Other studies have also emphasised the importance of experience: novice bidders often bid early and reactively, while experienced participants tend to employ more strategic approaches such as sniping or automated bidding. This section highlights key behavioural traits and the influence of experience on bidding strategies, providing the foundation for a deeper analysis in the study.

2.4.1 Heterogeneity in Online Bidding Strategy

Over the past two decades, research on bidder behaviour in online auctions has evolved from traditional auction theory, which assumes that all bidders act rationally and homogeneously to maximize their net worth in single-item auctions, to more empirical studies that emphasize bidder heterogeneity in multi-item auctions. Challenging classical assumptions, numerous studies have identified distinct bidder types with varying motivations and strategies, often using clustering techniques to uncover patterns in bidder behaviour. This shift has provided a more nuanced understanding of how different bidding strategies impact auction outcomes, consumer surplus, and market efficiency.

- **Early Research on Bidder Heterogeneity**

Early research combined theoretical constructs with empirical observations to classify bidders, laying the foundation for identifying heterogeneity in online auctions (Bapna, Goes and Gupta, 2000; Hayne, Smith and Vijayasathy, 2003). Bapna, Goes and Gupta (2000) were the first to

theoretically analyse bid structures in multi-item online auctions, classifying bidders based on their expected revenue contributions and comparing these revenues to those generated by a hypothetical, more efficient auction mechanism. Their study also introduced theoretical characteristics that formed the basis for developing testable hypotheses on bidder behaviour.

Hayne, Smith and Vijayasathya (2003) extended this research by conducting a large-scale empirical analysis of over 11,000 eBay auctions. Their study classified bids and bidders based on bid timing, frequency, and strategic behaviour, offering insights into bidder participation dynamics and success rates in online auctions. This evolution in research has been driven by the need to understand how different bidder types influence key auction outcomes, such as winning probability and consumer surplus. The shift from theoretical models to empirically derived bidder classifications represents a significant advancement in auction research, providing a performance-based comparison of online bidders for the first time.

- **Applying Clustering Techniques**

Building on earlier studies that employed classification-based approaches, subsequent research has increasingly relied on clustering methodologies to analyse bidder heterogeneity. The application of ML algorithms, such as K-means clustering, has enabled researchers to identify distinct bidder groups, revealing that heterogeneous bidding strategies can have significantly different impacts on auction performance.

Shah *et al.* (2003) used clustering techniques in SAS Enterprise Miner™ to analyse bidding patterns in eBay video game console auctions, identifying established and emerging strategies. Their analysis introduced new attributes such as number of bids, bid timing and excess

increment, enabling the classification of distinct bidder clusters based on behavioural patterns. Additionally, they applied association rule analysis to detect potential shill bidding, though no strong correlation was found between specific bidding behaviours and fraudulent activities.

Bapna *et al.* (2004) used a data-driven, inductive method to develop a more detailed taxonomy of bidding behaviour in online auctions. They identified five distinct strategies: Early Evaluator, Middle Evaluator, Opportunist, Sip-and-Dipper, and Participator. By analysing data from online auctions, they examined three strategic variables: Number of Bids (NOB), Time of Entry (TOE), and Time of Exit (TOX). Their findings demonstrated that these bidding strategies significantly affect both the chances of winning and the consumer surplus, thereby enhancing the understanding of bidder heterogeneity in online auctions.

- **Development of Research**

Subsequent studies have expanded on the three foundational criteria—number of bids (NOB), time of entry (TOE) and time of exit (TOX)—established by Bapna *et al.* (2004), integrating additional behavioural features and adapting the framework to new auction environments. These advancements have broadened the analytical scope and enhanced the ability to capture nuanced bidder strategies in online auctions. Shang, Chen and Cheng (2006) introduced jump bids, where bidders place bids higher than the minimum required to gain an advantage, and identified four bidder types—Observers, Adventurers, Opportunists and Early Players—each exhibiting distinct timing behaviours. Using the C5.0 decision tree algorithm, they developed classification rules to differentiate bidders and found that auction pacing significantly influences bidding activity. Although jump bids were initially included as a classification

variable, they were ultimately excluded from the final model due to their redundancy with bid frequency, suggesting they do not independently influence bidder categorization.

Bapna *et al.* (2009) introduced the concept of overlapping auctions and examined how market-level factors, such as price information from prior auctions, degree of overlap, auction format and overall market supply, affect auction prices. Using K-means clustering, they segmented bidders at the auction level based on entry and exit timing and bid revisions, classifying them into Evaluators, Opportunists and Participators. At the market level, bidders were categorized as individual or institutional bidders based on total participation, average bid revisions, and average quantity demanded. Their findings reveal that bidder heterogeneity exists both within individual auctions and across the broader market, with auction overlap significantly lowering final prices. Notably, information about future auctions exerts a stronger negative influence on prices than past auction data, highlighting the strategic nature of bidder behaviours in competitive auction environments.

Expanding research into online sequential auctions, Goes, Karuga and Tripathi (2012) analysed bidding strategies, identifying Active Bidders, Evaluators, and Opportunists based on number of bids, time of entry and exit, and time between auctions as clustering criteria. They further distinguished recurrent bidders, who consistently engaged across multiple auctions, from intermittent bidders, who participated selectively with the time between auctions (TLA). Their findings demonstrated that demand heterogeneity, participation experience, and auction design significantly shape bidding behaviour, with experience driving bidders toward late bidding strategies. Specifically, single-unit bidders often started as Evaluators but evolved into

Opportunists, whereas multi-unit bidders predominantly maintained opportunistic strategies to capitalize on market trends and auction dynamics.

Adomavicius *et al.* (2012) explored the role of real-time information feedback in continuous combinatorial auctions, demonstrating its significant impact on bidding behaviour. Using a data-driven approach, they investigated how bidders respond to auction complexity through three experimental feedback treatments. To identify distinct bidder strategies, they conducted cluster analysis based on four key behavioural variables: time of entry, number of bids, number of distinct bundles bid on, and exploratory analysis (measured as mean clicks per bid). Their analysis revealed three stable bidder strategies—Analyzers, Participators and Explorers—consistently observed across all treatments and remaining robust across separate experiments with different setups, further reinforcing their validity.

Chang (2012) expanded on previous findings by examining bidder interdependencies across overlapping auctions, moving beyond the individual auction level. Using a two-phase approach, they combined K-means clustering with a dynamic systems model to analyse bidder behaviour at both the auction mechanism and market levels. In Phase 1, clustering based on time of entry, exit, and bid revisions identified three bidder types: Evaluators, Opportunists, and Participators. In Phase 2, these clusters were integrated into a dynamic systems model to examine transition patterns, long-term behaviour, and equilibrium states in overlapping auctions. This analysis provided insights into how bidder distributions evolve over time, reinforcing the importance of market-level dynamics in auction research.

Chang (2014) further analysed bidder strategies in multiple overlapping online auctions (MOOAM) using entropy analysis to measure bidding heterogeneity. Through k-means clustering, bidders were classified at the individual auction level into Evaluators, Opportunists, and Participators, based on entry time, exit time, and bid revisions, and at the market level into individual and institutional bidders, with institutional bidders influencing price outcomes through market monitoring. The study found that auction overlap significantly affects bidder behaviour, with greater overlap increasing market visibility and strategic adjustments.

Lu *et al.* (2016) examined bidder heterogeneity focused on multichannel sequential B2B auctions, identifying five bidding strategies—Conservative Early Bidders, Conservative Opportunists, Analyzers, Forward-Looking Early Bidders and Forward-Looking Opportunists—through cluster analysis using clustering variables of time of entry, time of exit, and daily bid frequency. They found that budget constraints, demand, and transaction costs shape strategic choices. High-budget bidders favoured early bidding, while demand-driven bidders adopted analytical or opportunistic strategies. Opportunists, particularly those using online channels, leveraged market awareness and strategic patience, ultimately achieving higher surplus extraction in sequential auctions

In secondary market B2B auctions, Pilehvar, Elmaghraby and Gopal (2017) examined how market information influences bidder behaviour in secondary market B2B auctions, particularly the role of first bids in shaping final auction prices. Analysing 5,355 online auctions, they identified two key sources of pricing information: historical bidding behaviour (past winning prices) and real-time price signals from overlapping and recently completed auctions. Using clustering analysis, they classified bidders into Regular bidders, who bid infrequently and are

less responsive to market conditions, and Super-bidders, who bid frequently and strategically adjust to real-time price signals. Their findings suggest that experienced bidders leverage concurrent auction prices in their bidding strategies, with first bids playing a critical role in determining final prices. Furthermore, bidders often transition from regular to super-bidder status as they gain experience, highlighting the learning effects in online auction markets.

While other studies extend their research, Cui and Lai (2013) investigated bidding strategies in online single-unit auctions, identifying three primary strategies: Early Bidding, Snipe Bidding, and Agent-supported Ratchet Bidding. Using data from Taobao.com, they analysed both objective and subjective measures to evaluate the impact of these strategies on auction outcomes, including winning probability, cost savings, and bidder satisfaction. Their findings revealed that while these strategies led to varying levels of cost savings and winning success, they had no significant impact on perceived bidder enjoyment. The study also confirmed that bidder satisfaction is influenced by the effectiveness of their chosen strategy, reinforcing the importance of strategic decision-making in online auctions

Cui *et al.* (2020) extended this analysis by applying the Motivation-Opportunity-Ability framework to examine how bidder factors influence strategy adoption in single-unit auctions. Using survey data from Taobao.com, they identified agent bidding, snipe bidding, and ratchet bidding as the three dominant strategies. Their findings demonstrated that hedonic and utilitarian motivations, time availability, bidding experience, and risk preference all significantly affect the choice of bidding strategy. Notably, risk-averse bidders were more likely to engage in ratchet bidding, while experienced bidders favoured snipe bidding. This study

highlighted the complex interplay between individual bidder characteristics and strategic behaviour, offering insights for both auction design and bidder decision-making.

- **Methodological innovations**

While previous studies have applied similar frameworks across different settings, Peng and Müller (2008) criticized the clustering criteria established by Bapna *et al.* (2004) for failing to incorporate actual bid amounts, arguing that such inclusion would improve clustering accuracy. To address this, they introduced a distance-based clustering method designed for sparsely observed bidding behaviours in online auctions. Their methodology employed a customized distance metric tailored for irregularly sampled longitudinal data, allowing for a refined classification of bidder strategies based on bid amounts, time of entry and exit, and frequency of bids. Through this approach, they identified six distinct bidding patterns, each linked to varying probabilities of securing an auctioned item at a favourable price. The study emphasized the importance of dynamic bidding behaviour analysis, showing that bidders adjust their strategies in response to auction conditions, competition, and personal objectives.

Based on Peng and Müller (2008), Hayne, Bugbee and Wang (2010) analysed bidder behaviours in eBay auctions, comparing collectibles (1968 Chevrolet Camaros) and commodities (digital cameras). using functional data analysis and distance-based clustering with Partitioning Around Medoids. They categorized bidders into Snipers and Sentry-Snipers based on bid timing, frequency, and intensity. Their findings showed that sniping dominated both categories, especially in commodity auctions, where late bidders had a higher success rate. In contrast, Sentry-Snipers were more common in collectibles, likely due to price discovery and item uniqueness considerations. The study also found that auction duration had little impact on

bidding behaviour, while product type significantly influenced strategy selection, with sniping being more extreme in commodity auctions. These insights underscore the strategic nature of late bidding and its implications for auction design, seller pricing, and bidder decision-making

Uniquely, Mancha *et al.* (2014) used finite mixture partial least squares (FIMIX-PLS) to segment online auction bidders based on behavioural patterns and personality traits without predefined groupings. Analysing English and Vickrey auctions, they identified four bidder types—Hedonic bidders, Vigilant bidders, Participators, Opportunists—in each format using bid frequency, increments, impulsivity, sensation-seeking, and web skills. Their findings showed that bidder enjoyment and willingness to pay varied by personality, with hedonic bidders showing high participation and enjoyment, while vigilant bidders used strategic late bidding with minimal increments. The study emphasized how risk tolerance, competitiveness, and auction rules influence strategies, underscoring the importance of behavioural insights in auction platform design and optimization.

Table 2.3 summarises existing studies on bidder heterogeneity and identifies key gaps. Most prior research has followed the behavioural framework of Bapna *et al.* (2004), with K-means clustering as the dominant method. While bid increment patterns are commonly analysed, feedback scores have rarely been considered as a proxy for bidder experience. Crucially, no existing studies have used datasets involving certified remanufactured products. The only partial exception is Pilehvar, Elmaghraby and Gopal (2017), which focused on used and returned items. This study fills that gap by examining bidder segmentation in remanufactured product auctions, where signalling and information asymmetry are especially pronounced.

Table 2.3: Summary of Literature on Bidder Heterogeneity in Online Auctions

Article	Bidder Groups	No. of Criteria	Bid Frequency	Bid Timing		Bid Increment	Experience	K-means Clustering	Dataset	Remark
				Time of Entry	Time of Exit					
Shah, Joshi, Sureka & Wurman (2003)	Evaluate, Skeptic, Snipe, Unmask	3	✓	✓		✓			Video Game Console	Clustering using SAS Enterprise Miner™
Bapna, Goes, Gupta & Jin (2004)	Early Evaluators, Middle Evaluators, Sip-and-Dippers, Participators, Opportunists	3	✓	✓	✓			✓	Computer Hardware & Consumer Electronics	Applied in multi-item auctions.
Shang, Chen & Cheng (2006)	Observers, Adventurers, Opportunists, Early Players	4	✓	✓	✓			✓	Computer Products	Used C5.0 decision tree to classify bidders and detect shill bidding.
Peng & Müller (2008)	Low-End, High-End, Slow Start, Fast Start slow increase, Aggressive, Early	3	✓	✓	✓			✓	Personal Digital Assistants	Applied distance-based clustering for sparse biddings.
Bapna, Chang, Goes & Gupta (2009)	Evaluator, Opportunist Participator, Individual Bidders, Institutional Bidders	3	✓	✓	✓			✓	Speaker, DVD & Home theatre	Applied in overlapping auctions at individual and market levels.
Hayne, Bugbee & Wang (2010)	Sniping, Hybrid (Sniping + Sentry)	3	✓	✓	✓			✓	Chevrolet Camaro & Digital Camera	Used PAM clustering to distinguish snipers and hybrid bidders.
Adomavicius, Curley, Gupta & Sanyal (2012)	Analyzers, Participators, Explorers	4	✓	✓				✓	Experiment	Conducted lab experiments on real-time feedback in combinatorial auctions.

Chang (2012)	Early Evaluators, Opportunists, Active Participants	3	✓	✓	✓			✓	Electronics	Longitudinal study on bidder transitions in overlapping auctions.
Goes, Karuga & Tripathi (2012)	Early Evaluators, Middle Evaluators, Opportunists, Participators, Early Evaluators, Middle Evaluators, Opportunists	4	✓	✓	✓			✓	Various Categories	Studied bidder adaptation in sequential auctions.
Cui & Lai (2013)	Early Biding, Snipe Bidding, ASR Bidding	4	✓						Various Categories	Classified single-unit auction
Chang (2014)	Evaluator, Opportunist, Participator	3	✓	✓	✓			✓	Electronics	Used entropy analysis in overlapping auctions.
Mancha, Leung , Clark & Sun (2014)	Hedonic, Vigilant, Participators, Opportunistic	5	✓			✓			Experiment	Applied FIMIX-PLS
Lu, Gupta, Ketter & van Heck (2016)	Early bidders, Opportunists, Analyzers	4	✓	✓	✓			✓	Flowers	Analysed in sequential B2B auctions.
Pilehvar, Elmaghraby & Gopal (2017)	Cluster 1, Cluster 2	5					✓	✓	Electronics (Used & Returned)	Applied in secondary B2B markets.
Cui, Lai, Lowry & Lei (2020)	Ratchet, Agent, Snipe	4	✓	✓		✓		✓	Various Categories	Clustering from online survey data.

2.4.2 Different Bidding Strategy by Experience

Bidder experience significantly shapes bidding strategies, risk preferences, and overall success rates in online auctions. Experienced bidders tend to refine their approaches over time, optimizing their bidding behaviour based on previous outcomes and market conditions.

- **Late Bidding**

A growing body of research has explored how bidder experience influences bidding strategies, with particular attention to sniping—the practice of placing bids in the final moments of an auction. Wilcox (2000) provided one of the earliest empirical studies on this phenomenon, showing that experienced bidders favour sniping, strategically delaying their bids to minimize price escalation and increase their chances of winning. In contrast, inexperienced bidders place multiple incremental bids throughout the auction, often revealing their valuation and inviting competition. These findings suggest that bidders refine their strategies through experience, shifting from frequent early bidding to more calculated late-stage bidding over time.

Expanding on these insights, Roth and Ockenfels (2002) compared eBay's hard-close auctions with Amazon's soft-close auctions, showing that eBay bidders frequently placed last-minute bids, while Amazon bidders bid more gradually due to automatic auction extensions, which discourage sniping by giving competitors more time to respond. Their findings emphasized that sniping is a rational strategy in hard-close auctions, where bidders wait until the last second to prevent competitive reactions and avoid triggering additional bidding activity. However, Amazon's soft-close structure reduces the effectiveness of sniping, leading to more evenly distributed bidding behaviour.

Ockenfels and Roth (2006) further examined how auction rules shape bid timing, reinforcing earlier findings. Their study confirmed that hard-close auctions strongly encourage sniping, while soft-close auctions result in more evenly distributed bidding since last-minute bids trigger an auction extension. The research demonstrated that bidders adapt their strategies to platform-specific rules, emphasizing the role of auction design in shaping bidding behaviour. Supporting this, Ariely, Ockenfels and Roth (2005) experimentally tested auction ending rules, confirming that fixed-ending auctions (e.g., eBay) promote sniping, while dynamic-ending auctions (e.g., Amazon) discourage it by allowing last-minute bids to extend the auction. Their study reinforced the idea that bid timing is shaped by auction design, aligning with earlier findings.

Adding to this, Borle, Boatwright and Kadane (2006) analysed bid timing and multiple bidding behaviours across various product categories, finding that experienced bidders either bid early or engage in sniping, strategically minimizing their participation in incremental bidding. In contrast, inexperienced bidders place frequent incremental bids, increasing competition and driving up final prices. This suggests that bid frequency and timing serve as indicators of bidder expertise, with experienced bidders demonstrating greater strategic efficiency by formulating a single, well-timed bid instead of engaging in potentially costly multiple bidding.

Examining the impact of sniping on auction prices, Hou (2007a) found that sniping results in lower final prices, as it limits competitive counterbidding and prevents price escalation. Early-entry winners tend to pay higher prices compared to last-minute bidders, highlighting the strategic advantage of sniping in securing lower prices. These findings further confirmed that late bidding can be a cost-saving strategy, regardless of auction type.

Unlike previous studies, Wang and Hu (2009) explored how winning and losing experiences influence bidding behaviour using panel data from new eBay users, showing that losing an auction drives bidder toward more efficient strategies, placing fewer incremental bids and shifting toward sniping. In contrast, winning an auction does not necessarily improve bidding strategies, as winners tend to maintain their existing habits regardless of efficiency. This suggests that loss-driven learning is a key factor in bidding refinement, while winners, lacking the same incentive to adjust, continue with their established behaviours.

Shifting the focus to novice bidders, Livingston (2010) found that inexperienced eBay users tend to bid early and frequently, often leading to higher final prices. Novice bidders are also more likely to engage in emotional bidding, continuously raising their bids to stay ahead rather than making rational cost-benefit calculations. Over time, however, bidders learn to navigate auction dynamics more strategically, transitioning from frequent early bidding to late-stage sniping. This reinforces the idea that effective bidding strategies develop through repeated auction participation.

More dynamically, Goes, Karuga and Tripathi (2012) investigated bidding behaviour evolution in sequential auctions, categorizing bidders into Active Bidders, Evaluators, and Opportunists. Their study found that new bidders initially favour early bidding but gradually transition toward sniping as they gain experience. This shift highlights a learning process, where bidders refine their strategies to minimize competition and optimize pricing over time. Their findings align with theoretical equilibrium predictions, reinforcing the importance of sequential learning in shaping bidder behaviour.

Expanding the perspective on bidder heterogeneity, Pilehvar, Elmaghraby and Gopal. (2017) examined the role of market information, highlighting that experienced bidders are more adept at integrating past transaction data and price trends into their bidding strategies. Their study found that seasoned bidders strategically adjust their bids based on historical and real-time price signals, leading to more efficient and predictable bidding behaviour. In contrast, novice bidders rely on trial-and-error learning, lacking the ability to leverage market data effectively. These findings reinforce that experience enhances auction intelligence, allowing bidders to time their bids strategically and optimize their outcomes.

Shifting the focus to soft-close auctions, Cao *et al.* (2019) examined sniping behaviour in auctions with extended closing rules, demonstrating that while sniping is most prevalent in hard-close settings (eBay), it also occurs in soft-close auctions (Overstock). The key distinction is that in soft-close auctions, bidders time their snipes just before the extension trigger, rather than at the absolute end of the auction. This study reinforced that sniping is a learned strategy, with bidders adapting their tactics based on platform-specific rules and auction mechanisms.

Finally, Cui *et al.* (2020) explored how bidder experience influences strategy selection, finding that experienced bidders prefer automated bidding (agent-supported), whereas novice bidders engage in frequent manual bidding. Using the Motivation-Opportunity-Ability framework, their research demonstrated that experience leads to more calculated and less reactive bidding behaviour, improving auction efficiency. The study also highlighted that individual bidder factors, including experience, risk preference, and intrinsic motivations, determine the adoption of different bidding strategies, such as sniping, agent bidding and ratchet bidding.

The collective findings highlight the critical role of experience in shaping bidding behaviour, particularly the shift from early, frequent bidding to strategic late-stage sniping. While hard-close auctions encourage last-minute bidding, soft-close auctions alter its timing by allowing bid extensions. Additionally, auction design, past experiences, and market signals influence bidder strategies, with experienced bidders optimizing their approach to minimize costs and enhance winning probabilities. Ultimately, bidding strategies evolve through experience, leading to more efficient and calculated decision-making over time.

- **Rational Bidding**

Experience in online auctions significantly shapes bidding behaviour, influencing both bid timing and the tendency to overbid. As bidders gain experience, they refine their strategies, transitioning from impulsive and reactive bidding to more calculated and rational approaches, ultimately improving auction efficiency.

Simonsohn and Ariely (2008) investigated herding behaviour in eBay auctions, demonstrating that inexperienced bidders frequently misinterpret the presence of existing bids as a signal of higher quality, leading them to follow the crowd and drive-up prices in low-starting-price auctions. However, experienced bidders are more discerning, recognizing and avoiding such biases by evaluating auction signals more critically. This highlights how experience mitigates irrational bidding behaviours and underscores the importance of auction design and information transparency in shaping bidder decision-making.

Similarly, Srinivasan and Wang (2010) examined how repeated participation refines bidding strategies, showing that accumulated experience—rather than simple reliance on feedback

scores—gradually aligns bidding behaviour with theoretical auction equilibrium. Their study found that inexperienced bidders tend to engage in reactive, incremental bidding, whereas experienced bidders develop more deliberate, rational strategies over time. Notably, they confirmed that losing an auction serves as a stronger driver of learning than winning, as it forces bidders to reassess their strategies, avoid previous mistakes, and refine their decision-making in subsequent auctions.

Supporting these, Kostandini *et al.* (2011) analysed eBay data and confirmed that experienced bidders consistently secure lower prices compared to their novice counterparts. Their findings indicate that experience enhances a bidder's ability to navigate auctions effectively, reducing overbidding tendencies and improving efficiency. Expanding on this, Pownall and Wolk (2013) examined internet art auctions and found that repeated participation leads to a significant reduction in bid amounts, with bidders who participate in ten or more auctions lowering their bids by up to 26%. This study suggests that experienced bidders learn to time their bids more effectively, avoiding unnecessary competition and price escalation, further reinforcing the idea that bidding expertise develops through ongoing engagement with auction dynamics.

However, Ow *et al.* (2018) provided a contrasting perspective, demonstrating that while experience increases trust in auction platforms, it can paradoxically lead to higher bid levels. Their study found that experienced bidders, particularly those with selling experience, exhibit greater confidence in the auction mechanism, leading them to place higher bids due to their trust in the platform's reliability. This suggests that while experience often enhances efficiency, its effects on bidding behaviour are complex and context dependent.

The relationship between experience and overbidding is multifaceted, with research demonstrating both its mitigating and reinforcing effects. Hou, Kuzma and Kuzma (2009) examined the winner's curse and adverse selection in online auctions, revealing that high uncertainty increases the risk of overbidding, while low uncertainty leads to adverse selection, where high-quality items struggle to attract competitive bids due to bidder scepticism. Their study found that experienced bidders are better at managing quality uncertainty, utilizing available information more effectively, and reducing their likelihood of overpaying.

Easley, Wood and Barkataki (2010) focused on experience in rare coin auctions, demonstrating that experienced bidders strategically lower their bids in anticipation of greater competition, aligning with theoretical predictions of common-value auctions. Their findings indicate that domain-specific experience, rather than general auction experience, is a stronger predictor of successful bid adjustments, as experienced bidders recognize uncertainty and incorporate it into their decision-making to avoid overpayment.

Feng, Fay and Sivakumar (2016) provided further evidence that experience reduces overbidding, showing that bidders with extensive auction participation exhibit lower frequencies and magnitudes of overbidding. Their study found that product-category-specific experience plays a particularly strong role in mitigating overbidding tendencies, as bidders develop familiarity with price trends and optimal bidding strategies. However, they also noted that highly competitive environments can still trigger overbidding, particularly among less experienced participants. These findings suggest that experience fosters more rational bidding behaviour, leading to improved market efficiency and reduced impulsive decision-making.

Conversely, Malmendier and Lee (2011) challenged the notion that experience alone mitigates overbidding, showing that even seasoned bidders frequently pay more than fixed-price listings for the same item. Their findings suggest that psychological factors, such as the excitement of winning, play a crucial role in driving overbidding, demonstrating that auctions often attract bidders willing to overpay. Similarly, Garratt, Walker and Wooders (2012) examined second-price auctions and found that even highly experienced eBay users deviate from true-value bidding. While novices tend to overbid, experienced bidders exhibited both underbidding and overbidding tendencies, indicating that real-world auction experience does not always lead to optimal bidding behaviour.

Table 2.4 summarises key studies on how bidder experience influences auction behaviour, revealing that experience consistently leads to more strategic and late-stage bidding. Experienced bidders tend to adopt refined tactics such as sniping and last-minute bidding to reduce competition and secure better price outcomes, whereas novice bidders are more susceptible to incremental bidding, emotional decision-making, and overbidding due to competitive arousal. These behavioural contrasts underscore the critical role of experience in shaping auction dynamics and enhancing overall market efficiency. While prior bidder heterogeneity studies have rarely incorporated experience as a primary clustering criterion, this section emphasises its importance by demonstrating clear strategic differences between experienced and inexperienced participants.

Table 2.4: Summary of Literature on the Impact of Bidder Experience in Online Auctions

Article	Methods	Results
Late bidding		
Wilcox (2000)	Empirical analysis	Experienced bidders are more likely to place bids at the very end of an auction.
Roth & Ockenfels (2002)	Comparative analysis of eBay and Amazon data	Sniping is prevalent in hard-close auctions (eBay), while soft-close auctions (Amazon) lead to more evenly distributed bidding.
Ariely, Ockenfels & Roth (2005)	Experimental study	Fixed-ending auctions promote sniping, while dynamic-ending auctions reduce last-minute bidding.
Ockenfels & Roth (2006)	Empirical and theoretical analysis	Hard-close auctions strongly encourage sniping, whereas soft-close auctions distribute bidding more evenly over time.
Borle, Boatwright & Kadane (2006)	Econometric modelling	Experienced bidders strategically bid either very early or very late, while novices bid frequently throughout the auction.
Hou (2007a)	eBay transaction data analysis	Sniping results in lower final prices by limiting competitive counterbidding, while early bidding often leads to price escalation.
Wang & Hu (2009)	Panel data analysis	Losing experiences drive bidders to bid later and place fewer incremental bids, aligning behaviour with auction theory predictions.
Livingston (2010)	Empirical analysis of eBay transactions	Inexperienced bidders place early and frequent bids, leading to competitive overbidding, while experienced bidders strategically bid late.
Goes, Karuga & Tripathi (2012)	Empirical study of sequential auctions	Bidders shift from early bidding to sniping as they gain experience in sequential auctions.
Pilehvar, Elmaghraby & Gopal (2017)	Data-driven clustering analysis	Experienced bidders integrate past price trends into bid timing strategies, optimizing their approach over multiple auctions.
Cao, Sha, Yao, Gu & Shao (2019)	Empirical analysis of Overstock auctions	Sniping is prevalent in soft-close auctions as well, but bidders adjust their timing just before the extension trigger rather than at the absolute end.
Cui, Lai, Lowary & Lei (2020)	MOA framework	Experienced bidders prefer automated (agent-supported) bidding, whereas novices engage in manual bidding and frequent bid adjustments.
Rational Bidding		

Simonsohn & Ariely (2008)	Empirical analysis of eBay auctions	Inexperienced bidders exhibit herding behaviour, misinterpreting existing bids as a quality signal, whereas experienced bidders avoid such biases.
Hou, Kuzma & Kuzma (2009)	Empirical study of online auctions	High uncertainty leads to overbidding (winner's curse), while low uncertainty causes adverse selection; experienced bidders better manage quality risks.
Wang & Hu (2009)	Panel data analysis	Losing bidders refine their strategies by bidding later and placing fewer bids, while winning experiences do not necessarily improve strategies.
Easley, Wood & Barkataki (2010)	Empirical study of rare coin auctions	Experienced bidders adjust for the winner's curse by lowering their bids in anticipation of competition.
Srinivasan & Wang (2010)	Longitudinal analysis	Learning from repeated participation, rather than feedback scores alone, drives bidding behaviour closer to theoretical equilibrium.
Kostandini, Mykerezi, Tanellari & Dib (2011)	eBay transaction data analysis	Experienced bidders consistently secure lower prices compared to novices, confirming learning effects in auction participation.
Malmendier & Lee (2011)	Empirical study of eBay auctions	Over 42% of auctions exceed simultaneously available fixed prices, demonstrating that even experienced bidders engage in overbidding.
Garratt, Walker & Wooders (2012)	Experimental study of second-price auctions	Even highly experienced bidders deviate from true-value bidding, engaging in both overbidding and underbidding, indicating persistent strategic biases.
Pownall & Wolk (2013)	Longitudinal dataset analysis	Repeated participation leads to lower bid amounts; bidders with experience reduce bidding levels by up to 26%.
Feng, Fay & Sivakumar (2016)	Empirical analysis of electronic auctions	Experience mitigates overbidding; bidders with category-specific experience bid more efficiently, reducing both frequency and magnitude of overbidding.
Ow, Spaid, Wood & Ba (2018)	Experimental study with eBay field data	Experience increases trust in auction platforms, which can paradoxically lead to higher bids due to increased confidence in the mechanism.

2.4.3 Explainable Clustering

Although clustering is widely employed as an unsupervised ML technique to partition datasets based on similarity, interpreting its results remains challenging. This is because unsupervised methods often yield outputs without clear, detailed explanations, particularly when applied to complex data distributions. While metrics such as the Silhouette coefficient effectively quantify cluster quality, they provide little insight into the underlying factors driving specific groupings (Morichetta, Casas and Mellia, 2019).

To overcome this limitation, various approaches have been developed to enhance the interpretability of clustering outcomes. For instance, decision tree-based models inherently provide transparency through rule paths that explain cluster formation. Studies by Basak and Krishnapuram (2005), Fraiman, Ghattas and Svarc (2013), Loyola-Gonzalez *et al.* (2020), and Bertsimas, Orfanoudaki and Wiberg (2021) have demonstrated that such models can yield interpretable clusters. However, these methods are often constrained by the limitations of tree structures, which may not fully capture the complexity of the data.

Explainable clustering methods that leverage XAI techniques, particularly SHAP, offer model-agnostic, consistent, and detailed local interpretability for individual data points, making them highly practical for real-world applications. These techniques can be broadly divided into two categories: supervised and unsupervised. Although both approaches employ classification models based on the resulting cluster values to derive the underlying rules, they differ in how they handle the dataset input for clustering. In the supervised approach, data are first transformed into SHAP values using a classification model before clustering, whereas the unsupervised approach works directly on the raw feature data and then calculates SHAP values

with a classification model after clustering. Overall, by integrating clustering and classification within an explainable framework, this methodology bridges the gap between unsupervised data partitioning and interpretable, feature-based analysis, offering a more transparent and actionable understanding of complex datasets.

Explainable Supervised Clustering

Explainable Supervised Clustering is a unified framework that uses model-agnostic explanation techniques, typically SHAP, to transform input data into an interpretable feature space before applying clustering algorithms. This approach enables both transparency and predictive relevance by aligning clustering outcomes with underlying model behaviour. Lundberg *et al.* (2019) introduced the concept of supervised clustering, which involves performing clustering on a transformed space defined by SHAP values. This approach addresses two key limitations of traditional clustering methods: first, conventional distance metrics do not account for discrepancies in feature units, and second, unsupervised techniques often fail to adequately prioritize features that are most relevant to a specific outcome.

To overcome these issues, local explanation embeddings are used to map each sample into a novel “explanation space”, where clustering is then performed based on the model’s explanations. This supervised clustering method inherently accounts for differences in feature scales and emphasizes changes pertinent to the outcome. Molnar (2025) further underscores that clustering the Shapley values of individual instances yields groupings that directly reflect each feature’s contribution to the model’s output, thereby making the decision process more transparent and interpretable.

Explainable supervised clustering generally involves three-step process (Cooper, Doyle and Bourke, 2021; Cohen, Huan and Ni, 2024).

- 1) The dataset is transformed into an “explanation space” using SHAP values derived from a supervised model such as XGBoost. In this step, SHAP values are calculated for each instance to quantify the contribution of each feature toward the model’s outcome.
- 2) Clustering algorithms, such as K-means or DBSCAN, are applied within this explanation space to partition the data into homogeneous subclasses, effectively grouping instances that share similar patterns.
- 3) Interpretation rules-based cluster descriptions are generated to characterise each cluster using tools such as *SkopeRules*. These rules provide clear, high-coverage explanations that enhance the transparency and understanding of the identified clusters.

The evolution of explainable clustering methods is evident across multiple domains. In the insurance sector, Gramegna and Giudici (2020) pioneered the approach by clustering SHAP values to develop customer profiles and reveal underlying behavioural patterns. Building on this foundation, the healthcare domain has seen further advancements: Cooper, Doyle and Bourke (2021) applied supervised clustering on SHAP-transformed COVID-19 symptom data to identify distinct patient subgroups. In the area of fault diagnosis, Cilínio *et al.* (2023) leveraged a SHAP-based supervised clustering approach for analysing mobile network faults, and Cohen, Huan and Ni (2024) extended this framework to fault prognosis in manufacturing by generating interpretable decision rules. Complementing these, Ouyang, Liu and Han (2024) integrated XGBoost-SHAP with latent clustering and mixed logit models to uncover key factors influencing pedestrian injury severity, and in hydrology, Wang and Peng (2024) combined K-

means clustering with XGBoost and SHAP to improve runoff forecasting by capturing spatio-temporal heterogeneity. Together, these studies illustrate how grouping similar methods by domain not only refines the understanding of explainable clustering but also highlights its growing impact across diverse real-world applications.

Explainable Unsupervised Clustering

Explainable supervised clustering, as its name implies, transforms the dataset into SHAP values before clustering, thus incorporating supervision into the clustering process. In contrast, explainable unsupervised clustering partitions the raw data solely based on intrinsic patterns and subsequently employs classification models and SHAP to provide post hoc explanations for complex black-box models by revealing the underlying rationale behind cluster assignments (Morichetta, Casas and Mellia, 2019; Alvarez-Garcia, Ibar-Alonso and Arenas-Parra, 2024).

Typically, explaining clustering involves a three-step process (Morichetta, Casas and Mellia, 2019; Horel *et al.*, 2020; Bobek *et al.*, 2022).

- 1) First, an appropriate clustering algorithm, such as K-means or DBSCAN, is applied to unlabelled data, assigning each data point to a cluster based purely on intrinsic patterns.
- 2) Second, the resulting cluster labels are used as target variables to train a supervised classification model, effectively reframing the unsupervised clustering task as a supervised classification problem.
- 3) Finally, XAI techniques, including SHAP, LIME, or permutation feature importance, are applied to interpret the classifier's decisions, thereby uncovering interpretable and actionable rules that define each cluster.

Recent studies have advanced explainable clustering frameworks by combining unsupervised learning with interpretable ML techniques to reveal latent data structures and derive actionable insights across diverse domains. For instance, Morichetta, Casas and Mellia (2019) proposed the EXPLAIN-IT framework, which first embeds unlabelled data using unsupervised clustering, then applies support vector machines (SVMs) for classification. Local Interpretable Model-agnostic Explanations (LIME) is subsequently used to provide human-understandable, instance-level explanations of the decision boundaries. Horel *et al.* (2020) addressed the lack of interpretability in financial applications by combining clustering algorithms such as K-means and DBSCAN with a supervised classifier. They introduced the Single Feature Introduction Test (SFIT) to identify statistically significant variables that characterise each cluster, enhancing transparency in regulatory compliance tasks.

Bobek *et al.* (2022) introduced CIAMP (Cluster Analysis with Multidimensional Prototypes), a method that replaces traditional centroid-based cluster explanations with multidimensional bounding boxes. This approach captures arbitrary cluster shapes and produces precise, rule-based explanations suitable for complex industrial scenarios. Alvarez-Garcia, Ibar-Alonso and Arenas-Parra (2024) developed a four-stage framework integrating data preprocessing, dimensionality reduction, clustering, and classification, implemented in the open-source Python package “Clust-learn”. Tested on educational assessment data, the framework enables interpretable analysis of high-dimensional, heterogeneous datasets.

In the healthcare domain, Lau *et al.* (2022) applied unsupervised clustering to blood test results from COVID-19 patients in Hong Kong. The approach uncovered distinct clinical phenotypes, enabling better patient stratification and informing triage decisions based on age, mortality risk,

and comorbidities. In environmental science, Xu *et al.* (2024) integrated K-means clustering with XGBoost-SHAP to study spatial heterogeneity in glacier melt across Tibet. The model quantified the influence of geographic and climatic factors on regional melt patterns, supporting adaptation strategies for climate resilience and water resource planning.

In transportation safety, Yassin and Pooja (2020) developed a hybrid model combining K-means clustering with Random Forest classification to predict road accident severity in Addis Ababa. By introducing cluster-derived features, the model achieved 99.86% accuracy and highlighted key risk factors such as driver experience and vehicle age. Sun *et al.* (2024a) and Wang *et al.* (2024) used Latent Class Analysis (LCA) in conjunction with XGBoost-SHAP to identify behavioural segments influencing traffic violations and crash-related delays. Their models revealed distinct patterns driven by seasonal effects, road types, and driver characteristics, offering guidance for data-informed policy interventions. Sun *et al.* (2024b) examined truck drivers' perceptions of safety climate using data from over 7,000 individuals. By comparing five clustering algorithms and employing SHAP, Permutation Feature Importance (PFI), and a novel Quantitative Partial Dependence Plot (QPDP) method, the study found that supervisory safety promotion was the key factor distinguishing driver groups.

Collectively, these studies demonstrate the growing utility of explainable clustering techniques—leveraging SHAP, SFIT, LIME, bounding boxes, and QPDP—in transforming complex, opaque ML outputs into interpretable insights. These methods bridge the gap between unsupervised learning and real-world decision-making across finance, healthcare, transportation, safety, education, and environmental sustainability.

Table 2.5 summarises the existing literature on explainable clustering, covering both supervised and unsupervised learning approaches. It outlines which clustering techniques, dimensionality reduction methods, classification algorithms, and XAI tools (e.g., SHAP or LIME) were used in each study. In relation to the third research question of this study—bidder heterogeneity in online auctions for remanufactured products—the table highlights a clear gap in the literature, as no prior studies have addressed this specific context. The types of datasets used in previous research further illustrate the lack of attention to this area. Additionally, some methodological patterns emerge from the literature: studies employing K-means clustering often use PCA for dimensionality reduction, while those using XGBoost for classification typically rely on SHAP for interpretability. These trends provide a useful methodological framework for this study to build upon.

Table 2.5: Summary of Literature on Explainable Clustering

Article	Dataset	Clustering methods			Dimensional Reduction		Classifier	XAI methods		Remarks
		K-means	DBSCAN	LCA	PCA	UMAP	XGBoost	SHAP	LIME	
Explainable Supervised Clustering										
Gramegna & Giudici (2020)	Insurance	✓			✓		✓	✓		Integrates XGBoost and SHAP , using K-means for customer segmentation
Cooper, Doyle & Bourke (2022)	COVID-19 Symptoms		✓			✓	✓	✓		A SHAP -driven supervised clustering combining XGBoost , UMAP for dimensionality reduction, HDBSCAN for cluster detection, and SkopeRules for rule extraction.
Cilínio, Pereira, Duarte, Mata & Vieira (2023)	Mobile Network		✓			✓	✓	✓		A SHAP -based supervised clustering using LightGBM for fault prediction, UMAP for dimensionality reduction, and DBSCAN for discovering fault clusters
Cohen, Huan, & Ni (2024)	Health		✓			✓		✓		Leverages an Artificial Neural Network enhanced with SHAP , integrate UMAP and HDBSCAN for clustering, and employs SkopeRules to extract rules.
Ouyang, Liu & Han (2024)	Pedestrian Injury			✓			✓	✓		Uses XGBoost and SHAP for feature selection, LCA for segmentation, and mixed logit for subgroup analysis.
Wang & Peng (2024)	Hydrology	✓					✓	✓		Integrates XGBoost with SHAP and K-means clustering
Explainable Unsupervised Clustering										
Morichetta, Casas & Mellia (2019)	YouTube	✓							✓	Combines multiple clustering methods (Agglomerative ward & single, K-means, BIRCH) and SVM -based labelling, with LIME .
Horel, Storchan, Giesecke & Chittar (2020)	Wealth Management									Uses Agglomerative hierarchical clustering , followed by Neural Network classification and SFIT for rule-based explanations.

Yassin & Pooja (2020)	Road Accident	✓						✓		Implements a hybrid approach where K-means extracts latent patterns and Random Forest predicts accident severity.
Bobek, Kuk, Szelążek & Nalepa (2022)	Various Publicly Available Datasets						✓			Combining clustering (Gaussian Mixture, BIRCH, Deep Temporal Clustering) with XGBoost classification and prototype representation using multidimensional bounding boxes, with interpretable rule extraction via the HeaRTDroid engine.
Lau, Ng, Kwok, Tsia, Sin, Lam & Vardhanabhuti (2022)	COVID-19 Clinical Phenotypes	✓ (based)			✓			✓		Utilises K-prototype clustering with PCA for dimensionality reduction and applies LightGBM with SHAP for model explanation.
Alvarez-Garcia, Ibar-Alonso & Arenas-Parra (2024)	Education (Student Dataset)	✓			✓		✓	✓		Integrates dimensionality reduction (SPCA, MCA), clustering (K-means, Agglomerative, GMM), and XGBoost classification with SHAP to generate explainable clusters
Sun, Lan, Goh, Safiena, Huang, Lytle, & He (2024a)	Safety Climate	✓	✓					✓		Compares multiple clustering techniques (DBSCAN, K-means, Agglomerative, Mean Shift, BIRCH) and applies Gradient Boosting with SHAP for post-clustering interpretability.
Sun, Wang, Qi, Wang, Gu, Wang, Lu, & Chen (2024b)	Traffic Violation			✓			✓	✓		Integrates LCA for segmentation and XGBoost with SHAP
Wang, Jiao, Wang, Luo & Lu (2024)	Crash Data			✓			✓	✓		Leverages LCA for segmentation, combined with XGBoost and SHAP
Xu, Tian, Gao, Yan & Liu (2024)	Land Use	✓					✓	✓		Combines K-means clustering with PCA and XGBoost-based SHAP

2.5 Economic Theories

This section of the literature review examines key economic theories of information asymmetry, which is heightened in online auctions for remanufactured products due to the combined uncertainty of product condition and the nature of digital transactions. Understanding the mechanisms through which this asymmetry arises and the role of signalling in mitigating its effects is a central objective of this study.

2.5.1 Information Asymmetry

Information asymmetry arises when one party in a transaction has more or better information than the other, leading to inefficiencies or potential market failures. Foundational research on this issue began in the 1970s, with seminal contributions from George Akerlof, Michael Spence, and Joseph Stiglitz. Their work introduced critical concepts such as adverse selection, signalling, and screening, recognised with the 2001 Nobel Prize in Economics.

These theoretical frameworks offer critical insights into how markets operate under conditions of imperfect information and suggest mechanisms to mitigate resulting inefficiencies. Applying these principles to the context of online auctions, particularly those involving remanufactured products, this study investigates how information asymmetry can be reduced in environments characterised by uncertainty and the absence of physical inspection. In such high-risk settings, where buyers face heightened ambiguity about product condition and remanufacturing quality, the study explores the signalling roles of various informational cues, including seller feedback, certification, and return policies. The objective is to determine which of these signals most effectively enhance transparency and promote efficiency in digital transactions.

- **Adverse Selection in Online Market**

Akerlof's influential work (1970) introduced the concept of adverse selection, illustrating how information asymmetry between buyers and sellers can lead to market failure. In markets where buyers cannot reliably assess product quality, such as the used car market he examined, buyers tend to base their offers on the average expected quality. This discourages sellers of high-quality goods, who are unable to receive appropriate compensation, ultimately resulting in a market dominated by low-quality products, or "lemons". Akerlof's theory underscores the critical role of information in maintaining market efficiency. This concept is directly relevant to online auctions for remanufactured products, where buyers often face significant uncertainty regarding item condition and quality, increasing the risk of adverse selection and inefficiency.

Adverse selection in online markets occurs when buyers cannot verify product quality before purchase, leading to undervaluation of high-quality goods and reduced market efficiency. Studies show that uncertainty drives price discounts (Dewan and Hsu, 2004) and deters high-quality sellers, particularly in luxury (Gulati *et al.*, 2009) and B2B secondary markets (Alhauili, Elmaghraby and Gopal, 2022). Reputation systems and feedback mechanisms can mitigate these effects. Saeedi (2019) and Hui, Saeedi and Sundaresan (2018) found that stronger reputation signals reduce low-quality participation, while Klein, Lambertz and Stahl (2016) showed that transparency improves seller behaviour, collectively confirming that clear quality signals are key to addressing adverse selection.

The following section explores the issue of information asymmetry in both online marketplaces and remanufactured product markets. It examines how the lack of transparent and verifiable information, particularly regarding product quality and seller credibility, can distort buyer

perceptions and hinder efficient transactions. Furthermore, this section investigates a range of signalling strategies designed to mitigate these asymmetries, such as reputation systems, quality certifications, return policies and detailed product disclosures.

2.5.1.1 Information Asymmetry in Online Marketplace

With the rapid expansion of e-commerce, information asymmetry has emerged as a critical issue that influences buyer behaviour, pricing strategies, and overall market efficiency. Online commerce inherently creates information asymmetry, as buyers are unable to physically assess product quality or reliably gauge seller trustworthiness. Consequently, website signals become the primary means by which both product quality and seller reliability are communicated (Huston and Spencer, 2002; Mavlanova, Benbunan-Fich and Koufaris, 2012).

In the absence of physical interaction, e-commerce buyers rely heavily on information provided by sellers, such as product descriptions, images and customer reviews. However, this information is often incomplete or biased, increasing buyer uncertainty about product quality (Pavlou, Liang and Xue, 2007). This uncertainty contributes to adverse selection, where buyers, sceptical of product claims, assume the goods may be of lower quality than advertised. As a result, they may offer lower bids or avoid transactions altogether (Dimoka, Hong and Pavlou, 2012). This behaviour discourages high-quality sellers from participating in the market, leaving lower-quality products to dominate, a phenomenon of “Lemon Market” (Akerlof, 1970).

The design of online auctions can amplify the effects of information asymmetry, particularly through the mechanism of auction duration. Muthitacharoen and Tams (2017) demonstrated that shorter auction durations exacerbate information asymmetry by restricting the time

available for buyers to investigate product details or evaluate seller credibility. This time pressure often leads to rushed decisions and suboptimal pricing outcomes. In contrast, longer auctions reduce information gaps by affording buyers greater opportunity to gather relevant information, verify claims and assess quality, thereby promoting more informed bidding behaviour and improving price accuracy.

2.5.1.2 Information Asymmetry in Remanufactured Product Markets

Information asymmetry remains a fundamental barrier in the remanufactured goods market, as consumers often lack clear insight into product quality, the scope of refurbishment, and the credibility of the remanufacturer. This challenge is particularly acute in online settings, where the intangible nature of e-commerce, combined with the inherent uncertainty surrounding remanufactured products, further widens the informational gap. This section builds upon the previously discussed attributes by examining the distinctive features specific to remanufactured products that contribute to this uncertainty.

- **Uncertainty from the Remanufacturing Process**

Remanufacturing is often perceived as a “black box”, a process largely invisible to the consumer (Hazen *et al.*, 2012). For individuals with low tolerance for uncertainty, this opacity heightens concern over hidden defects and past usage intensity (Wang *et al.*, 2013). The result is a downward adjustment in perceived value, even when the physical product may be of high quality. Moreover, the unobservable nature of the refurbishment process forces consumers to rely on incomplete signals when evaluating product reliability (Tereyağoglu, 2016). This structural opacity fuels quality-related doubts. To mitigate these concerns, scholars emphasise the importance of clear, standardised, and verifiable information about remanufacturing

procedures. Enhancing visibility into the process can reduce perceived risk and improve consumer acceptance by bridging the informational gap at its source (Abbey *et al.*, 2015).

- **Uncertainty in the Quality**

Consumers frequently associate remanufactured products with lower quality compared to new equivalents, despite the remanufacturing processes aimed at restoring products to ‘like-new’ conditions (Abbey *et al.*, 2017). The perception gap primarily arises from uncertainties about the lifespan, performance, serviceability, and intrinsic value of remanufactured goods, causing inflated risk perceptions and misconceptions (Hazen *et al.*, 2017). Abbey *et al.* (2017) further elaborate that consumers’ perceived risk in remanufactured products is significantly influenced by functional and cosmetic defect concerns, directly affecting their WTP.

Additionally, consumers’ tolerance for ambiguity notably influences their purchasing behaviour; those with higher ambiguity tolerance show greater openness to purchasing remanufactured products (Wang *et al.*, 2018). Singhal, Jena and Tripathy (2019) confirm that perceived risk negatively affects purchase intentions, particularly due to uncertainties regarding product reliability and performance. Perceived quality, which includes factors like performance, reliability, and durability, is critical in shaping purchasing intentions for remanufactured products (Sun *et al.*, 2018). Higher perceived product quality positively influences consumer attitudes toward environmental protection and increases purchase intentions, emphasising the need for clear communication of quality assurances (Sun *et al.*, 2018; Wang *et al.*, 2018). In contrast, perceived risk due to the uncertainty of remanufactured products negatively impacts these positive attitudes, further complicating consumer acceptance (Sun *et al.*, 2018).

2.5.2 Methods for Mitigating Information Asymmetry

To address adverse selection, two primary strategies—signalling and screening—are employed. Spence (1973) introduced the concept of signalling in his work on job market signalling. Spence proposed that individuals or firms with more information (such as sellers) can use signals—credible actions or attributes that convey information about product quality. Similarly, Stiglitz (1975) expanded on this concept with screening, where the less-informed party (buyers) attempts to extract information from the more-informed party (sellers).

The fundamental difference between them lies in who initiates the process and bears the associated cost. Signalling, introduced by Spence (1973), involves the informed party actively conveying credible information to the less-informed party. In contrast, screening, as described by Stiglitz (1975), requires the less-informed party to seek out and verify information, incurring the cost themselves. In the context of online auctions for remanufactured products, signalling is the more relevant strategy for addressing information asymmetry. Since buyers cannot physically inspect items before purchase, sellers (the informed party) must provide credible signals to assure buyers (the less-informed party) of product quality and reliability.

2.5.2.1 Signalling in Online Marketplace

In online environments, where buyers cannot physically inspect goods, signalling mechanisms play a vital role in reducing information asymmetry and fostering trust between buyers and sellers. Key signals include reputation systems, feedback mechanisms, product descriptions, number of pictures, warranties, and return policies. These signals help buyers make more informed decisions in an environment where direct interaction with sellers or products is not possible, ultimately enhancing market efficiency and trust.

- **Seller Reputation and Product Ratings**

In online markets characterised by high information asymmetry, seller reputation and product ratings operate as primary market signals to reduce uncertainty and facilitate trust-based transactions. Anchored in signalling theory (Spence, 1973), reputation serves as an observable and interpretable cue that allows buyers to infer seller quality in environments where direct verification is infeasible.

High reputation scores are consistently associated with higher price premiums, greater sales likelihood, and increased bidder engagement, particularly in markets where buyers cannot inspect products directly (Resnick *et al.*, 2006; Houser and Wooders, 2006; Van Der Heide, Johnson and Vang, 2013). Even a single instance of negative feedback can significantly disrupt future sales performance, underscoring the weight buyers place on reputational cues (Cabral and Hortacsu, 2010). Notably, the signalling effect of reputation is asymmetrical: negative reviews exert a stronger influence than positive ones, serving as a critical filter for avoiding perceived risk rather than identifying superior sellers (Standifird, 2001). Buyer trust also depends more on detailed, seller-specific feedback than on aggregated ratings, highlighting the importance of specificity in reputation systems (Zhang, 2006).

Reputation further interacts with other market signals such as warranties or third-party certifications. In the absence of more verifiable indicators, reputation serves as a key substitute in reducing uncertainty. However, when strong alternative signals are present, its marginal effect diminishes, suggesting a complementary role in multi-signal environments (Dewally and Ederington, 2006). Despite its value, reputation systems face several limitations, including

inflated ratings, retaliation bias, and the underreporting of negative experiences, that undermine their reliability. Without robust design and monitoring, such systems may fail to curb opportunistic behaviour, reducing their effectiveness as trust-building mechanisms (Dellarocas, 2005; Tadelis, 2016).

As a widely visible and summarised indicator, product ratings play a central role in mitigating information asymmetry by signalling perceived product quality. However, their reliability as quality indicators is subject to important limitations. Li and Hitt (2010) demonstrate that ratings often conflate perceived value with actual quality, especially in platforms that employ simplified, one-dimensional rating systems. Kim (2021) finds that the effect of ratings diminishes when stronger quality cues, such as brand reputation or expert reviews, are available, suggesting that ratings function more as compensatory signals in high-uncertainty contexts. Similarly, Li *et al.* (2015) show that consumers tend to rely more heavily on overall ratings than on detailed sub-scores, favouring simplified evaluations over nuanced assessments.

Despite their salience, ratings are prone to distortions. Empirical studies have identified common issues such as rating inflation, valence bias, and excessive reliance on average scores. For example, Cui, Lui and Guo (2012) find that negative reviews tend to exert a stronger influence than positive ones, while Wang *et al.* (2020a) show that emotionally charged or subjective language in reviews can skew perceptions of quality. Collectively, these findings underscore the need to interpret ratings cautiously, particularly in markets where accurate quality assessment is critical to consumer decision-making.

- **Warranties and Return Policies**

In digital marketplaces where physical product inspection is not possible, warranties play a vital role in reducing information asymmetry and enhancing buyer confidence. As signalling theory suggests, warranties are effective because they are both costly and credible—only sellers confident in their product’s quality can afford to offer meaningful post-sale commitments (Mavlanova, Benbunan–Fich and Benbunan–Fich, 2012; Bakshi, Kim and Savva, 2015). This makes warranties strategic tools for distinguishing high-quality sellers from their lower-quality counterparts. Their signalling strength is context dependent. Studies show that experienced consumers tend to interpret warranties as quality indicators, while less experienced buyers rely more heavily on them when other signals, such as brand reputation or detailed product descriptions, are weak or ambiguous (Srivastava and Mitra, 1998; Li *et al.*, 2015). Warranties thus serve a compensatory function in environments where trust is difficult to establish.

Empirical evidence supports their market effectiveness. Warranties have been shown to increase bid frequency and final prices in auctions (Shen, Chiou and Kuo, 2011) and are particularly appealing to risk-averse consumers who view them as insurance against post-purchase failure (Jindal, 2015). However, their credibility hinges on clarity—vague or misleading warranties can erode trust and increase customer dissatisfaction (Hu, Rabinovich, and Hou, 2015). Warranties are most impactful when used in combination with other trust-enhancing signals, such as seller ratings or third-party certifications (Dewally and Ederington, 2006). When clearly communicated and strategically deployed, warranties not only reassure buyers but also improve market efficiency by promoting informed decision-making in high-uncertainty transactions.

Return policies in online market have evolved into vital strategic instruments that not only manage post-purchase logistics but also serve as powerful market signals, effectively reducing information asymmetry and shaping consumer perceptions. By offering generous return options, online retailers signal their confidence in product quality and commitment to customer satisfaction, which, in turn, bolsters consumer trust and positively influences purchase intentions. For instance, studies have shown that comprehensive return policies, such as those allowing full refunds, can alleviate consumers' perceived risk and enhance their willingness to buy, even in the absence of physical inspection of the product (Moshrefjavadi *et al.*, 2012; Hsiao and Chen, 2012). Furthermore, lenient return policies have been found to interact synergistically with other trust-building mechanisms; Chang, Cheung and Tang (2013) illustrate that such policies work in tandem with reputation systems and third-party certifications to create a robust foundation of trust in online vendors.

Return policies also play a critical role in conveying quality signals. Bonifield, Cole and Schultz (2010) demonstrate that high-quality e-tailers tend to adopt more lenient return policies for non-consumable products, thereby differentiating themselves from lower-quality competitors. Similarly, Pei, Paswan and Yan (2014) find that consumers perceive full return policies as fairer compared to partial return policies, which significantly drives higher purchase intentions. In addition, return policy attributes such as return window length have been shown to signal service quality and retailer commitment; Rao *et al.* (2017) reveal that extended return windows boost consumer trust and WTP, albeit with diminishing marginal returns that suggest the existence of an optimal return period. Complementing these insights, Zhang *et al.* (2017) dissect return policy components and confirm that a combination of a long return window and a full refund policy is most effective in signalling high service quality.

- **Quality Cues (Textual and Visual)**

Quality cues play a critical role in shaping consumer behaviour in online markets by reducing information asymmetry and increasing WTP. Van Heijst, Potharst and Van Wezel (2008) were among the first to demonstrate the predictive power of natural language, showing that the content of product descriptions more accurately forecasted final auction prices than traditional seller reputation metrics. This early evidence positioned descriptive text as a key trust signal, capable of mitigating buyer uncertainty. Challenging the assumption that visual cues dominate online decision-making, Kim and Lennon (2008) provided empirical support for the “verbal superiority effect”, revealing that buyers often derive greater confidence from well-crafted descriptions than from images alone. Shen, Chiou and Kuo (2011) categorised auction-based signals into three types—seller reputation, product condition, and argument quality—confirming that the linguistic quality of descriptions significantly affects buyer engagement, bidding frequency, and WTP. These textual signals help reinforce perceptions of product authenticity and quality, thereby enhancing trust in high-risk online environments.

Building on this, Onur, Bruwer and Lockshin (2020) highlighted the impact of provenance-verifying descriptions for non-perishable experience goods like wine. Their findings showed that such disclosures reduce perceived risk and improve both sales probability and price. Hu, Wei and Cui (2023) further underscored the importance of strategic alignment between textual content and market conditions, cautioning that the effectiveness of disclosures depends on factors such as market saturation and product category. Most recently, Xu, Zhuang and Jackson (2024) introduced the concept of strategic ambiguity in textual disclosure, especially for probabilistic goods such as blind boxes. Their study found that balancing clarity with a degree

of mystery can enhance engagement and stimulate demand, offering a novel perspective on how textual cues function in markets where uncertainty is part of the value proposition.

Visual cues, particularly high-quality product images, serve as critical substitutes for physical inspection in online marketplaces, helping to bridge the information gap and reduce perceived buyer risk. These cues offer tangible, observable indicators that facilitate trust in the absence of direct product experience. Gregg and Walczak (2008) highlighted the effectiveness of visual design elements in auction listings, demonstrating that listings with high-resolution images and multiple viewing angles significantly increase bidder engagement. Their findings emphasise that image quality, clarity, and visual diversity (including the use of video content) enhance a product's perceived credibility, particularly in high-uncertainty contexts. Supporting this, Li, Srinivasan and Sun (2009) found that listings featuring multiple product images reduce perceived product defect risk and uncertainty, thereby stimulating greater bidder participation. Lewis (2011) extended these findings by showing that the integration of detailed visual content with descriptive text has a positive effect on final auction prices. This combination increases transparency and reinforces trust in product reliability.

Further clarification was offered by Shen, Chiou and Kuo (2011), who classified auction signals into seller reputation, product condition, and argument quality. Their study revealed a strong association between detailed visual presentation and auction success, confirming that visual cues effectively mitigate buyer uncertainty. Similarly, Van der Heide, Johnson and Vang (2013) demonstrated that high-resolution imagery significantly enhances buyer confidence and likelihood of purchase. More recently, Xu, Zhuang and Jackson (2024) explored the interaction between visual and textual signals, concluding that the integration of structured written

descriptions with high-quality images improves pricing efficiency by reducing buyer hesitation. Their study suggests that auction platforms and sellers should adopt holistic disclosure practices, combining visual and linguistic clarity to foster trust and support competitive outcomes in online remanufactured product markets.

2.5.2.2 Signalling in Remanufactured Product Market

Signalling theory plays a crucial role in mitigating information asymmetry in the remanufactured product market, where concerns about product quality, performance, and reliability often deter potential buyers. Effective signalling strategies, including seller reputation, product ratings, warranties, and certifications, help address consumer uncertainty by clearly communicating product quality and trustworthiness.

- **Consumer Education**

Consumer education is widely recognised as a key strategy for increasing acceptance of remanufactured products, though its effectiveness depends on how it is implemented. Abbey *et al.* (2015) highlight those emotional responses, particularly consumer disgust and the perception of “usedness”, remain major barriers. Educational content must therefore address these emotional concerns, not just provide rational information. Wang and Hazen (2016) found that quality uncertainty is a central issue, with clear explanations about the remanufacturing process, such as what components are replaced and how quality is ensured, being critical for reducing perceived risk and improving perceived value. However, as Wang *et al.* (2020b) point out, not all information is equally effective; overly detailed descriptions of certain stages (e.g., recapture) may heighten consumer reluctance, stressing the need for carefully curated content.

Zhou, Xiong and Jin (2021) introduce a consumer education paradox: while education boosts WTP, excessive consumer demand may destabilise supply chains, especially in early market stages. A moderate, phased educational approach may thus be more sustainable. Abdulla *et al.* (2024) further suggest that physical exposure to remanufactured products, such as through retail displays, is significantly more effective than written descriptions in reducing consumer disgust and enhancing perceived quality. These findings indicate that experiential education may be essential for reshaping attitudes and encouraging adoption.

- **Seller Reputations and Product Ratings**

Seller reputations and product ratings are critical signals in the remanufactured product market, helping consumers assess product quality and reducing uncertainties associated with purchasing refurbished goods.

Seller reputation plays a critical role in shaping consumer perceptions and purchasing behaviour in the remanufactured product market. Subramanian and Subramanyam (2012) demonstrated that seller reputation significantly accounts for price differentials between new and remanufactured goods, with products remanufactured by OEMs or authorised facilities commanding higher prices than those from third-party remanufacturers, while warranty strength had minimal impact. Similarly, Pang *et al.* (2015) underscored reputation as a key determinant in narrowing the price gap between remanufactured and new products, especially for transactions involving non-authorised sellers. Casalin and Dia (2019) further noted that reputation, measured via feedback scores, effectively reduces information asymmetry in low-value auctions. However, for high-value items, signals such as return policies and OEM

certifications often substitute for reputation, highlighting a context-dependent hierarchy of trust cues. Across these studies, reputation consistently emerges as a key driver of demand.

Van Nguyen *et al.* (2020) identified Number of Service Failures and Number of Service Successes as relevant reputation metrics. Interestingly, a few negative reviews suppressed demand, whereas a large number paradoxically increased it, suggesting a non-linear relationship possibly linked to the vendor's popularity. Positive reviews had a weaker effect, reflecting consumers' negativity bias. Agostini *et al.* (2021) echoed this, showing that reputation enhances trust in refurbished smartphones by reducing perceived risks around quality, safety, and financial loss. Consumers showed greater intent to purchase from sellers known for fairness, reliability, and good service.

These findings collectively suggest that seller reputation is not only a trust-building mechanism but also a strategic asset. For firms in the remanufactured market, proactively managing and communicating reputation is essential for mitigating uncertainty and driving consumer demand.

Product ratings, encompassing star-based scores, written reviews, and emotional tone, serve as important market signals in the remanufactured goods sector. Van Nguyen *et al.* (2020) found that while ratings and review sentiment moderately influence demand forecasting for remanufactured products on Amazon, their effect is less pronounced than other indicators such as service failures or answered customer questions. Nevertheless, positive sentiment in reviews contributes additional interpretive value by capturing affective cues that numeric ratings alone cannot express.

Building on this, Ghosh *et al.* (2023) applied ML and sentiment analysis to reviews of refurbished laptops, showing that a combination of textual reviews and numerical scores helps identify key product attributes and guides consumer decision-making. Shi and Zhu (2024) further demonstrated that average product ratings signal perceived quality and remanufacturer credibility, particularly when reinforced by additional indicators such as featured product labels. While ratings improve consumer trust, their effect is more limited for third-party remanufacturers compared to OEMs. Zhai, Wang and Zhao (2024) conducted a large-scale analysis of 50,000 reviews of remanufactured mobile phones and revealed that review characteristics, such as length, content focus (e.g., usability, service quality) and emotional tone, significantly affect sales performance. Positive emotions like satisfaction and surprise enhance purchase intent, while negative emotions, especially anger, deter consumers.

Overall, product ratings and review sentiment act as multidimensional signals that reduce information asymmetry and influence consumer behaviour. When used in conjunction with other trust indicators, they play a critical role in shaping buyer confidence in remanufactured product markets.

- **Warranties and Return Policies**

Warranties and return policies are among the most effective mechanisms for mitigating consumer scepticism and perceived risk associated with remanufactured products.

Warranties serve as critical quality signals that help mitigate consumer scepticism and perceived risk associated with remanufactured products. In markets where concerns about product history, functionality, and reliability are prevalent, warranties offer reassurance and

enhance buyer confidence. They function not only as risk-reduction tools but also as strategic instruments that influence consumer perceptions and WTP. Srivastava and Mitra (1998) found that expert consumers interpret strong warranties as indicators of high product quality regardless of brand familiarity, while novice consumers rely on warranties primarily when seller reputation is well established. This highlights the contextual nature of warranty effectiveness across consumer segments. Subramanian and Subramanyam (2012) observed that although warranties are expected to increase perceived product value, their marginal effect weakens when strong seller reputation and remanufacturer identity are already present. Similarly, Pang *et al.* (2015) showed that warranties can narrow the price gap between new and remanufactured goods, especially for unauthorised vendors, though their influence declines when sellers have long-standing reputations or when return policies are also offered.

From a marketing perspective, warranties are critical in value positioning. Liao, Li and Cheng (2015) demonstrated that warranties allow manufacturers to command higher prices, countering perceptions that remanufactured goods are inferior. Alqahtani and Gupta (2017) further emphasised that warranty-backed strategies improve credibility and increase consumer trust especially when accompanied by guarantees such as full refunds. Strategically, warranties address consumer loss aversion, which is a key psychological barrier in remanufactured product adoption. Liao (2018) found that warranty offerings positively influence WTP by compensating for the risk of post-purchase dissatisfaction. Casalin and Dia (2019) also highlighted that for high-value remanufactured items, warranties can substitute for weaker reputation cues, particularly when other trust signals are lacking. Finally, Zhou and Gupta (2019) argued that warranties have long-term signalling effects, reinforcing perceptions of quality over time and enabling sellers to adjust pricing strategies as remanufactured products age.

Return policies play a crucial role in reducing perceived risk and uncertainty associated with remanufactured products, serving as an important post-purchase safeguard that directly impacts consumer decision-making. Flexible and transparent return options function not only as assurances of product quality but also as strategic tools that enhance consumer trust and facilitate market adoption. Empirical studies consistently affirm their influence on consumer behaviour. Pang *et al.* (2015) demonstrated that the availability of return policies is linked to a reduction in the price gap between new and remanufactured products, indicating their role in boosting consumer WTP. Interestingly, the effect of return policies differs by seller type. The study revealed that while return policies had minimal impact when offered by non-manufacturer-approved sellers, they significantly influenced buyer perceptions when provided by manufacturer-approved vendors, underscoring the importance of signal credibility.

Xu, Zeng and He (2017) further emphasised the importance of the after-sales phase, including return and refund mechanisms, in shaping consumer risk perception. Their findings indicate that well-defined return processes implicitly increase buyer confidence and purchasing likelihood. Similarly, Casalin and Dia (2019) found that in high-value remanufactured transactions, return policies often serve as more effective risk mitigators than seller reputation. This suggests that in high-stakes purchases, consumers place greater weight on explicit, enforceable policies than on reputational cues. Experimental evidence from Confente *et al.* (2021) also supports this view. Their research showed that lenient return policies significantly lower perceived risk and increase purchase intentions across both online and offline settings. These policies act as strong quality signals, particularly in digital marketplaces where physical inspection is not possible.

- **Quality Cues (Textual and Visual)**

Persistent consumer concerns over quality continue to hinder the broader acceptance of remanufactured products (Abbey *et al.*, 2015, 2017). To address these concerns, both textual and visual quality cues serve as critical signals that shape consumer perceptions and influence purchasing decisions.

Textual cues, particularly product descriptions, refurbishment details, and usage histories, play a central role in reducing information asymmetry and enhancing perceived product reliability. Clear, structured explanations about the remanufacturing process can increase trust by signalling transparency and competence. Frota Neto, Bloemhof and Corbett (2016) noted that while such descriptions exert limited influence on price for remanufactured goods, they are critical for shaping perceptions in used product categories, which often lack formal guarantees or certification. This suggests that remanufactured products may inherently benefit from baseline quality assurance, while used goods require stronger textual justifications. Mugge *et al.* (2018) provided further insight, showing that consumer WTP can be enhanced through informative narratives that explain the refurbishment process. However, their findings caution against over-disclosure—excessive mention of prior defects or technical repairs may undermine trust and increase perceived risk. Thus, effective textual signalling should strike a careful balance between transparency and reassurance.

Complementary findings from Van Nguyen *et al.* (2020) highlight the contextual nature of textual effectiveness. In high-involvement categories, such as electronics, persuasive and informative descriptions, significantly improve demand forecasts. However, their impact is

diminished in low-risk categories like small appliances, where consumers rely more on brand cues or price information, suggesting that the strategic deployment of textual information must consider product type, perceived risk, and consumer involvement to maximise its effect.

Visual cues are critical in shaping consumer perceptions of remanufactured products, particularly in online marketplaces where physical inspection is not possible. Xu, Zeng and He (2017) found that product images modestly enhance WTP by increasing familiarity, but their influence is secondary to textual information such as product condition and seller reputation. Visual cues primarily function to reduce uncertainty, rather than act as decisive factors in consumer decisions. However, their impact is nuanced. Mugge *et al.* (2018) demonstrated that signs of wear, such as scratches or discoloration, can significantly diminish consumer evaluations. Moreover, inconsistencies between visual and verbal signals (e.g., a product described as like new showing visible flaws) further erode trust. This underscores the importance of alignment between visual and textual claims to sustain consumer confidence.

The overall effectiveness of visual cues remains debated. Frota Neto, Bloemhof and Corbett (2016), along with Van Nguyen *et al.* (2020), concluded that images have limited predictive value in consumer decision-making, with buyers placing greater emphasis on text-based information. Abdulla *et al.* (2023) extended this critique by showing that physical exposure more effectively improves perceptions of remanufactured product quality and boosts WTP compared to static images, videos, or text. This was attributed to reduced feelings of disgust and enhanced perceptions of durability. Collectively, these findings suggest that while visual cues play a supportive role online, physical interaction remains more effective in overcoming psychological resistance and increasing demand.

This section synthesised key economic theories of information asymmetry to establish a conceptual foundation for examining buyer decision-making and pricing mechanisms in online auctions of remanufactured products. Anchored in the seminal works of Akerlof (1970), Spence (1973), and Stiglitz (1975), the chapter contextualised how adverse selection emerges when buyers lack the ability to verify product quality, especially in settings where inspection is impossible, as in e-commerce. The issue is further intensified in the remanufactured goods market, where consumer scepticism about prior usage, refurbishment quality, and product reliability widens the information gap. This digital and product-specific uncertainty makes trust-building mechanisms essential for facilitating efficient transactions and price accuracy.

To address the challenges posed by information asymmetry, prior literature identifies several key signalling mechanisms that sellers can employ to convey product quality and reduce buyer uncertainty, such as seller reputation, product ratings, warranties, return policies, and textual or visual quality cues. This study operationalises these theoretical constructs into observable auction features, including feedback scores, review sentiment, warranty and return terms, and descriptive content. These features are integrated into regression models for the first and second empirical analyses to evaluate their impact on price outcomes across overall listings and by remanufactured product condition. The analysis is further extended to evaluate how these signals shape bidder heterogeneity within the clustering of remanufactured product auctions, aiming to uncover the differentiated characteristics that define distinct bidder segments. By embedding these economic theories into the modelling architecture, the study produces insights that are both data-driven and grounded in established theoretical principles.

Chapter 3

Methodology

3.1 Introduction

Research methodology provides the overarching framework for systematically addressing a research problem, distinguishing itself from specific methods by focusing on the rationale behind their selection (Kothari, 2004). It ensures coherence in research design and allows for critical evaluation by others. A sound methodological discussion includes the study's purpose, research design, data sources, analytical techniques, and the justification for each decision, thereby supporting the overall rigour and credibility of the study.

This chapter provides a detailed explanations on how the research methodology used to meet the research questions and objectives outlined in Chapter 1. This chapter is structured as follows. Section 3.2 discusses the philosophical foundation of the study, adopting a positivist approach that emphasises objectivity and quantifiable outcomes. Section 3.3 explains the research design, highlighting the rationale for employing secondary data analysis as the most suitable approach for this study. Section 3.4 details the data mining method implemented to ensure a rigorous and systematic analysis process. Section 3.5 provides a summary of the chapter, reinforcing the methodological coherence of the study.

3.2 Research Philosophy

This section examines the research philosophy underpinning the thesis's methodology, highlighting its critical role in shaping the overall research design. The selection of an appropriate philosophical framework is fundamental, as it provides the conceptual basis for knowledge generation and interpretation. A well-defined philosophical framework enhances consistency and rigor, ultimately strengthening the validity of research findings.

Johnson and Clark (2006) highlight that business and management researchers must be conscious of their philosophical stance, as it significantly impacts both research decisions and the interpretation of findings. A thorough examination of the assumptions underlying human perception and understanding is essential for developing a robust research philosophy, which in turn guides the choice of methodological approaches, research strategies, and analytical techniques (Saunders, Lewis and Thornhill, 2019). Furthermore, Bryman (2016) stresses the importance of aligning the research philosophy with the study's objectives to ensure methodological coherence.

To structure its research design systematically, this study draws on the 'Research Onion' framework (**Figure 3.1**), developed by Saunders, Lewis and Thornhill (2019). The framework provides a multi-layered representation of key elements in research planning, including philosophical positioning, theory development, methodological choices, research strategies, time horizon, and data analysis techniques. Each layer is aligned with specific decisions in this study, including the adoption of a positivist paradigm, an inductive approach to theory development, and a mono-method quantitative design. This layered model offers a transparent and coherent overview of how the study was conceptualised and executed.

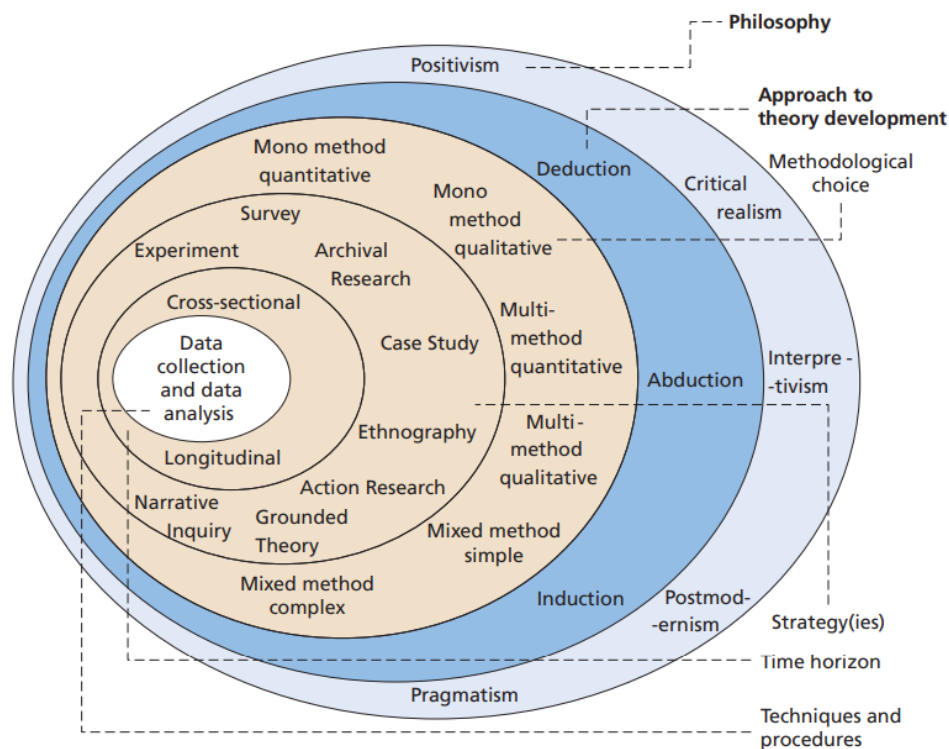


Figure 3.1: The 'Research Onion' Framework*

This thesis adopts a positivist research philosophy, which holds that reality exists independently of human perception and can be objectively observed, quantified, and analysed. Grounded in the empirical tradition of the natural sciences, positivism is widely employed in social science and business research, where knowledge is developed through systematic observation, hypothesis formulation, and statistical testing (Hughes and Sharrock, 2016; Saunders, Lewis and Thornhill, 2019). Under this paradigm, the researcher aims to uncover generalisable patterns that explain observable phenomena.

* Figure from Saunders, Lewis and Thornhill (2019)

To ensure philosophical coherence, this study aligns its ontological, epistemological, and methodological assumptions with the principles of positivism. This consistency strengthens the logical integrity of the research process and supports the internal validity, replicability, and transparency of the findings. These assumptions are further elaborated in the sections below.

- **Ontology**

This study is firmly rooted in the positivist paradigm, which asserts that an objective reality exists independently of human perception. This ontological stance aligns closely with the field of Big Data analytics, where vast datasets are systematically analysed to uncover empirically verifiable structures and regularities (Kitchin, 2014). By adopting this perspective, the research seeks to reveal objective truths about the remanufactured product market through quantification and scientific inquiry, ensuring both the accuracy and reliability of its conclusions.

Within the positivist framework, the availability of comprehensive, high-quality data is fundamental to developing a thorough understanding of complex phenomena (Saunders, Lewis and Thornhill, 2019). This is particularly relevant in the remanufactured product sector, where market dynamics are intricate, requiring advanced data analytics and data mining techniques to identify underlying interactions and dependencies among diverse market variables.

In the modern era, characterised by the exponential growth of Big Data, researchers face both the challenge of managing vast information volumes and the opportunity to gain unprecedented empirical insights (Kitchin, 2014). By focusing on objective, quantifiable patterns and measurable data, this study clarifies the structural and functional dynamics of the market. The positivist approach ensures that the research findings are reliable, replicable, and applicable

across various contexts, thereby offering valuable contributions to both theoretical models and practical market applications.

- **Epistemology**

This study adopts a positivist stance, emphasizing quantitative methods for both data collection and analysis. Positivism asserts that credible knowledge is derived exclusively from empirically verifiable and quantifiable phenomena (Crotty, 1998; Creswell and Creswell, 2018). This approach aligns closely with the Big Data paradigm, where vast datasets are analysed through computational techniques to generate novel insights (Kitchin, 2014). The primary objective is to uncover patterns and relationships that can be generalized across diverse contexts, adhering rigorously to the scientific method to ensure validity and reliability.

Consistent with data-driven science principles, this study employs advanced data mining techniques to analyse large-scale, measurable data. As Saunders, Lewis and Thornhill (2019) highlight, quantitative methodologies are indispensable for detecting complex patterns that qualitative approaches might overlook. The integration of Big Data analytics facilitates the identification of underlying market structures, offering a deeper understanding of bidder behaviour in auction markets.

By embracing positivist principles, this study ensures that quantitative methods are rigorously applied, producing findings that are objective, replicable, and data driven. The central role of data mining enables the extraction of meaningful trends from large datasets, while an iterative methodological approach allows for continuous refinement in response to new data. This adaptability is essential in evolving, data-intensive research environments (Kitchin, 2014).

Ultimately, adherence to positivist epistemology enhances the rigor, objectivity, and validity of the research. By focusing on empirical data and measurable phenomena, the study produces findings that are not only reliable but also widely applicable across various contexts, thereby reinforcing the credibility and impact of its contributions to the field.

- **Theory Development**

This study adopts an inductive approach to theory development, aligning with the principles of data-driven science. Inductive reasoning begins with specific empirical observations and progresses toward broader generalizations and theoretical frameworks (Saunders, Lewis and Thornhill, 2019). In the Big Data era, this bottom-up methodology allows theories to emerge directly from data analysis, rather than being constrained by preconceived hypotheses, ensuring that theoretical constructs remain firmly grounded in empirical evidence (Kitchin, 2014).

Given the study's focus on understanding bidder behaviour and identifying patterns in auction data, an inductive approach is particularly well-suited. The research systematically collects and analyses large-scale auction data on remanufactured products, uncovering underlying patterns that reveal bidder strategies and market dynamics. This process is enhanced through advanced data mining techniques and ML methods, which facilitate the discovery of hidden structures and relationships within the dataset. Consequently, the study moves from specific observations to the development of robust theoretical insights that accurately reflect real-world phenomena.

In the specific context of bidder behaviour on platforms such as eBay, the inductive approach begins with detailed data collection during the preparatory and modelling phases. Rigorous analysis of this data reveals recurring patterns, which subsequently inform the development of

theoretical propositions regarding auction dynamics and bidder strategies. The flexibility of the inductive approach enables the study to continuously refine theoretical frameworks as new data is incorporated, ensuring that emerging insights are systematically integrated into the overall analysis.

The iterative nature of this method is particularly effective in data-intensive research settings, where large datasets can uncover subtle patterns that traditional methods might overlook. As the study progresses, ongoing findings necessitate adjustments and refinements to the theoretical framework, ensuring that the resulting theories are robust, data-driven, and widely applicable to various market conditions.

Having established that this study embraces a positivist philosophy and has identified an inductive approach as the most suitable for theory and evidence development, the next section will articulate the research design employed to address the research questions and achieve the stated objectives. This section will provide a detailed account of the methodological framework, including data collection strategies, analytical techniques, and the procedural steps undertaken to ensure a rigorous and systematic inquiry. By offering a comprehensive overview of the research design, the study demonstrates how the chosen methods align with its philosophical and theoretical foundations, thereby reinforcing the robustness and validity of the findings.

3.3 Research Design

Following the philosophical foundation established in Section 3.2, this section outlines the research design that operationalises the study's objectives. Serving as both a strategic blueprint and a methodological framework, the research design defines the core elements necessary to systematically investigate the central research questions. Maintaining alignment between research questions and objectives is critical, particularly given the iterative nature of inquiry and the constraints imposed by the research timeline (Saunders, Lewis and Thornhill, 2019).

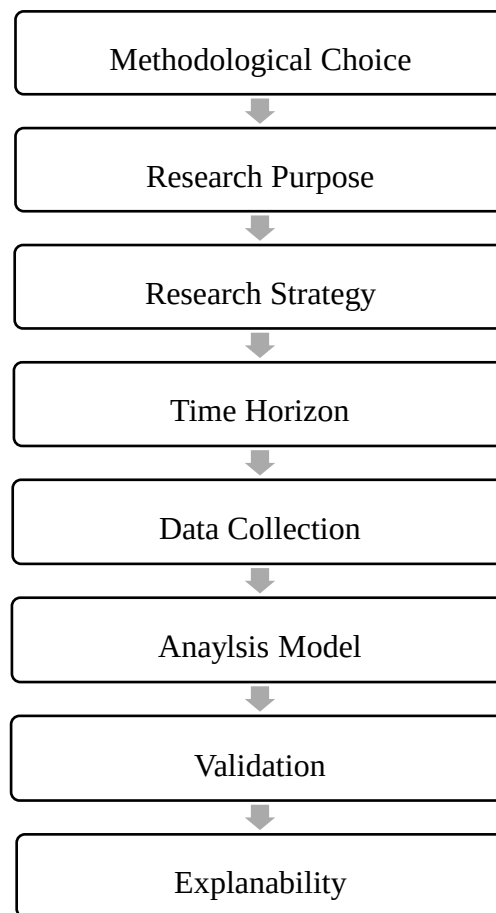


Figure 3.2: Framework of the Research Design

Figure 3.2 provides a visual representation of these components within the research design, offering a structured overview of the entire research process. This systematic approach ensures a thorough and methodical examination of the research topic, thereby facilitating the generation of robust and valid findings that contribute meaningfully to the field.

- **Methodological Choice**

To effectively address the research objectives and questions, this study adopts a quantitative methodological approach grounded in a positivist research paradigm. This choice is consistent with the study's epistemological stance, which prioritises objective measurement, empirical verification, and generalisability. Quantitative research is particularly appropriate for investigating behavioural patterns and market mechanisms within the context of online auctions for remanufactured products, where large-scale, structured data are readily available.

Quantitative methodologies are well-suited to data-rich environments, offering structured, scalable mechanisms for collecting and analysing large numerical data. This is particularly pertinent given the study's reliance on extensive transactional and behavioural datasets from online auctions. Such methods enable the identification of statistically significant patterns, segmentation of bidder profiles, and prediction of auction outcomes, while ensuring reproducibility and generalisability of findings (Saunders, Lewis and Thornhill, 2019).

Furthermore, the quantitative approach enables rigorous analysis of complex phenomena through objective, model-based techniques. It supports trend identification, model testing, and outcome prediction, essential in analysing large auction datasets. The use of established statistical and computational tools enhances both the reliability and external validity of the

findings (Creswell and Creswell, 2018). This study applies quantitative data mining methods to examine bidder behaviour: clustering algorithms identify distinct bidder types, regression models determine key bidding outcome drivers, and neural networks capture non-linear behavioural patterns (Kitchin, 2014). Together, these techniques provide a multifaceted view of auction dynamics.

By applying these tools, the study generates a multifaceted and empirically grounded analysis of online auction dynamics. This not only contributes to theoretical understanding but also yields actionable insights for practitioners, such as auction platform designers and sellers, aiming to optimise auction outcomes or tailor engagement strategies for different bidder segments. Ultimately, the adoption of a positivist, quantitative methodology ensures methodological coherence and analytical rigour. It reinforces the study's validity and supports the derivation of insights that are both academically robust and practically relevant.

- **Research Purpose**

Following the determination of the methodological approach, the study adopts an exploratory research strategy, appropriate for investigating complex and underexplored phenomena. Exploratory research is inherently open-ended and flexible, enabling the examination of areas where existing knowledge is limited. Its primary aim is not to test predefined hypotheses, but to identify patterns, uncover relationships, and generate new insights that may guide future theoretical development (Stebbins, 2001; Creswell and Creswell, 2018).

Within this context, the study adopts an exploratory strategy to uncover previously unobserved trends, correlations, and patterns that address existing research gaps from analyse large-scale

datasets. Specifically, ML techniques, such as tree-based regression and classification, and clustering, are applied to examine how market signals influence auction prices of remanufactured products and to identify key criteria that differentiate bidder segments that are not previously explored.

This strategy provides the empirical foundation for subsequent confirmatory research. By revealing novel patterns and generating data-driven insights, the exploratory approach supports the formulation of new hypotheses and the refinement of existing theories. It is particularly suited for data-rich, poorly understood domains, where flexibility is essential for meaningful discovery. Ultimately, the adoption of an exploratory strategy allows this study to advance understanding of bidder behaviour and market signalling in remanufactured product auctions on platforms like eBay. It also contributes to the broader theoretical discourse by offering empirical insights that bridge existing research gaps and inform future inquiry.

- **Research Strategy**

This study adopts an inductive research strategy consistent with the exploratory purpose and the positivist, quantitative methodological orientation. Rather than testing predefined hypotheses, the inductive approach derives generalisable patterns and theoretical insights directly from empirical observations (Saunders, Lewis and Thornhill, 2019). Unlike deductive reasoning, which begins with existing theory, this approach allows patterns and relationships to emerge from the data itself. Given the complexity and limited prior research on bidder behaviour in remanufactured product auctions, an inductive strategy is particularly appropriate.

The objective is to explore large-scale auction data to reveal new insights into bidder typologies, price determinants, and market dynamics. This approach complements the use of data mining and ML techniques, which are well-suited for uncovering structure in high-dimensional, unstructured datasets. Tools such as SHAP, clustering algorithms, and regression models are employed to detect non-linear relationships and latent behavioural patterns without reliance on existing theoretical frameworks.

By focusing on theory building rather than theory testing, the inductive strategy supports the identification of emergent phenomena in dynamic online auction environments, where traditional behavioural models often prove inadequate. The study context, characterised by pricing uncertainty, heterogeneous bidders, and evolving digital marketplaces, demands such empirical flexibility. Ultimately, this strategy enables the development of grounded insights into consumer behaviour and auction outcomes. It ensures that findings are derived from observed data, enhancing their validity, applicability, and contribution to both academic discourse and practical auction platform design.

- **Time horizon**

Defining the time horizon is a critical element of research design, as it shapes the temporal scope of data collection in line with the research objectives (Saunders, Lewis and Thornhill, 2019). This study employs a multiple cross-sectional design, wherein data are gathered at different time points from independent samples (Malhotra, Birks and Wills, 2017). Unlike longitudinal studies, which track the same subjects over time, this approach provides discrete snapshots of auction activity, capturing variability across changing market conditions.

The use of multiple cross-sectional data is particularly appropriate for analysing remanufactured product auctions. It enables the collection of diverse datasets across different time frames without necessitating repeated observations of the same bidders or items. Each dataset offers a point-in-time analysis of auction outcomes and bidder behaviour, contributing to a broader understanding of temporal dynamics within the market.

This design offers significant advantages in terms of flexibility and efficiency. It facilitates a robust examination of short-term bidding patterns and market responses, while avoiding the logistical and analytical complexity associated with longitudinal research. Although it does not allow for tracking individual behavioural changes over time, it is well-suited to the study's objective of identifying key factors influencing auction price across varying market contexts.

- **Data Collection**

Consistent with the study's positivist orientation emphasising empirical evidence and measurable data, this research utilises secondary data sourced from eBay. Data were collected through a combination of automated web scraping for publicly available auction information and manual extraction for elements not accessible via automation. These quantitative datasets serve as the empirical foundation for identifying objective patterns and relationships within the remanufactured product auction market.

The dataset comprises key numerical variables, including final auction price, starting price, number of bids, and bidder count—metrics essential for rigorous quantitative analysis. This use of secondary data aligns with the study's inductive strategy, enabling open-ended exploration without reliance on pre-established hypotheses. By examining extensive, real-world auction

data, the study aims to uncover behavioural patterns and market dynamics that inform theoretical development. The volume and granularity of the data allow for a comprehensive investigation of price determinants and bidder interactions, providing robust empirical grounding for the study's findings.

- **Analysis Model**

Aligned with the study's positivist philosophy and inductive, exploratory design, this research applies ensemble ML techniques with explainable artificial intelligence to analyse large-scale secondary data from online auctions of remanufactured products. These methods are well-suited to uncovering hidden patterns, behavioural structures, and variable relationships in complex datasets, particularly in the underexplored context of remanufactured goods.

The analytical framework of this thesis consists of three core methods—regression, clustering, and classification—each contributing distinct yet complementary insights into auction dynamics. Regression analysis is used to quantify the relationships between auction-specific variables such as final auction price and starting price, bidder count, and seller reputation, identifying key predictors of auction outcomes and supporting causal interpretation within a multiple cross-sectional design. Clustering, particularly through unsupervised techniques such as K-means clustering, enables the inductive identification of bidder heterogeneity by revealing natural groupings based on behavioural features such as entry timing, bid frequency and feedback scores, offering nuanced insights into strategic segmentation. Complementing this, classification models are employed to categorise bidders or predict auction outcomes based on observable characteristics, using supervised learning to generalise from labelled data.

By integrating these three analytical layers, this study constructs a robust and explainable data mining framework. This approach not only deepens theoretical understanding of bidder behaviour and auction pricing but also generates practical insights for sellers and platform designers seeking to optimise auction design and strategy.

- **Validation**

Validation, in line with the study's positivist research philosophy, serves as a critical mechanism to ensure that knowledge claims derived from empirical analysis are both objective and reliable. Under this paradigm, knowledge is considered valid when it is verifiable through systematic observation, replicable procedures, and measurable outcomes. Thus, validation is not merely a technical step, but a philosophical commitment to truth-seeking through evidence-based reasoning.

From an inductive logic perspective, where theory emerges from data rather than being imposed upon it, validation becomes essential to distinguish meaningful patterns from spurious correlations. Given the data-driven, exploratory nature of this study, validation ensures that the insights uncovered are not artefacts of noise or overfitting but rather grounded in stable relationships that hold across varied contexts or samples. This aligns with the epistemological stance that robust generalisations must emerge from consistent empirical regularities.

Furthermore, in an exploratory data mining context, validation plays a demarcation role, helping to separate signal from noise in the absence of predefined hypotheses. It acts as a safeguard against overinterpretation, ensuring that emergent findings meet criteria for internal consistency and external applicability. Rather than asserting universal truths, validation under

this framework supports probabilistic inference, indicating which patterns are likely meaningful and worthy of further theoretical development.

- **Explainability**

In alignment with the study's positivist philosophy and inductive research approach, explainability serves a critical epistemological function—it bridges the gap between complex algorithmic outputs and human interpretability, ensuring that insights derived from data are transparent, rational, and justifiable. From a positivist standpoint, knowledge must be empirically grounded and logically explained; thus, explainability ensures that models are not only predictive but also understandable in terms of causal or behavioural mechanisms.

In inductive research, where theory emerges from observed patterns, explainability enhances the theoretical relevance of findings by making visible the relationships and variable interactions that underpin model outcomes. It transforms black-box models into tools for knowledge generation, allowing researchers to extract not just results, but structured explanations informing practice and theory. Tools like SHAP are essential in this regard that they support the development of XAI by quantifying feature contributions, aligning complex models with the principles of transparency, replicability, and empirical reasoning.

3.4 Research Method

Research methods refer to the specific techniques and procedures employed to investigate a research problem, serving as the practical implementation of research methodology. They guide the processes of data collection and analysis. In the context of data mining research, selecting an appropriate methodological framework is essential for ensuring a structured and systematic approach to effectively address the research questions.

This study adopts the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework, a widely recognized methodology in data analytics that has remained the leading standard for knowledge discovery projects since its development in the late 1990s (Martínez-Plumed *et al.*, 2021). Its structured approach, business relevance, and adaptability make it a widely preferred framework (Chapman *et al.*, 2000; Kotu and Deshpande, 2019; Martínez-Plumed *et al.*, 2021). CRISP-DM provides several advantages over alternative data mining methods, such as SEMMA (Sample, Explore, Modify, Model, Assess) and KDD (Knowledge Discovery in Databases) as follows:

- 1) **Cross-Industry Applicability:** CRISP-DM is vendor-independent, offering cross-industry and cross-platform flexibility, with successful applications in finance, medicine, and manufacturing, underscoring its versatility (e.g., Wiemer, Drowatzky and Ihlenfeldt, 2019; Kolyshkina and Simoff, 2021; Plotnikova, Dumas and Milani, 2022; Bokrantz, Subramaniyan and Skoogh, 2023; Cheng, 2023). In contrast, SEMMA is tied to SAS Enterprise Miner, restricting its adaptability to SAS-based environments.
- 2) **Business Problem-Centric Approach:** With its Business Understanding phase, CRISP-DM ensures that data mining efforts focus on real-world problems rather than just technical analysis (Chapman *et al.*, 2000). This structured approach helps bridge the gap

between business goals and data science (Martínez-Plumed *et al.*, 2021). SEMMA and KDD, in contrast, prioritize data processing and modelling but lack strong business integration (Han, Kamber and Pei, 2012).

- 3) **Structured and Iterative Process:** CRISP-DM has six phases, and the iterative approach enhances the flexibility and adaptability of data mining workflows (Wirth and Hipp, 2000). While KDD lacks clear guidelines for data preprocessing and transformation, SEMMA emphasizes modelling and evaluation but is less aligned with business objectives (Fayyad, Piatetsky-Shapiro and Smyth, 1996; Kotu and Deshpande, 2019).
- 4) **Emphasis on Model Deployment:** CRISP-DM's Deployment phase ensures effective model implementation in business settings, thereby enhancing the practical impact of data mining. SEMMA lacks detailed deployment strategies, while KDD focuses more on knowledge discovery rather than model operationalization (Han, Kamber and Pei, 2012).

Figure 3.3 presents the CRISP-DM framework (Chapman *et al.*, 2000), which consists of six fundamental phases: Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment. Each phase includes a structured set of tasks designed to guide the practitioner from the initial problem definition to the generation of actionable insights. In this study, the CRISP-DM framework serves both as a procedural guide and a conceptual foundation for structuring the thesis. The entire analytical process is applied in alignment with the research objectives and thesis format.

The Business Understanding phase is embedded in the Introduction and Literature Review chapters, which establish the theoretical groundwork, articulate the research motivation and objectives, and formulate the core research questions. With the exception of the data collection

process, most of the technical components, including Data Understanding, Data Preparation, Modelling, and Evaluation, are addressed within this chapter. Meanwhile, the specific data characteristics and processing strategies tailored to each empirical study, as well as the modelling outcomes and interpretative analyses relevant to each research theme, are discussed separately within the corresponding empirical analysis chapters. This structure ensures that both methodological rigour and contextual relevance are maintained throughout the thesis.

Business Understanding	Data Understanding	Data Preparation	Modeling	Evaluation	Deployment
Determine Business Objectives Background Business Objectives Business Success Criteria Assess Situation Inventory of Resources Requirements, Assumptions, and Constraints Risks and Contingencies Terminology Costs and Benefits Determine Data Mining Goals Data Mining Goals Data Mining Success Criteria Produce Project Plan Project Plan Initial Assessment of Tools and Techniques	Collect Initial Data Initial Data Collection Report Describe Data Data Description Report Explore Data Data Exploration Report Verify Data Quality Data Quality Report	Select Data Rationale for Inclusion/ Exclusion Clean Data Data Cleaning Report Construct Data Derived Attributes Generated Records Integrate Data Merged Data Format Data Reformatted Data Dataset Dataset Description	Select Modeling Techniques Modeling Technique Modeling Assumptions Generate Test Design Test Design Build Model Parameter Settings Models Model Descriptions Assess Model Model Assessment Revised Parameter Settings	Evaluate Results Assessment of Data Mining Results w.r.t. Business Success Criteria Approved Models Review Process Review of Process Determine Next Steps List of Possible Actions Decision	Plan Deployment Deployment Plan Plan Monitoring and Maintenance Monitoring and Maintenance Plan Produce Final Report Final Report Final Presentation Review Project Experience Documentation

Figure 3.3: Overview of the CRISP-DM Process*

* Figure from Chapman *et al.* (2000)

3.4.1 Data Understanding

This phase involves gaining an initial understanding of the dataset through data collection, description, exploration, and quality assessment. It begins with collecting relevant data aligned with the research objectives, followed by summarising its structure and key characteristics. Exploratory analysis is conducted to identify patterns, trends, or anomalies, while data quality checks ensure completeness, accuracy, and consistency. In this study, the methodology chapter focuses specifically on data collection techniques, while data description, exploration, and quality assessment are addressed in the relevant analytical chapters.

3.4.1.1 Data Collection

This section details the data collection methods employed in the study, which are critical components of the Data Understanding phase. The success of any data mining project relies heavily on the acquisition of accurate and reliable data, making effective data collection indispensable. Sophisticated techniques enable systematic planning and execution, thereby facilitating robust research outcomes (Olsen, 2012).

To collect the necessary data, the study selected eBay as the primary data source for auction data on remanufactured electronics, utilising a Python-based web scraping method that integrated Selenium WebDriver with BeautifulSoup. This approach allows efficient and structured extraction of transaction data, resulting in a comprehensive dataset suitable for analysis. Selenium WebDriver, a toolset for automating web browser interactions, provides programmatic control over browser actions through browser-specific drivers. In this study, ChromeDriver was employed to execute the data collection process, facilitating seamless interaction with eBay's web pages. BeautifulSoup, a Python library for parsing HTML and

XML content, was used to extract the necessary information from the web pages accessed via Selenium. The integration of these tools facilitated the automation of complex web interactions and ensured accurate extraction of structured data for analytical purposes.

It is important to emphasize that, in compliance with eBay's policies, web scraping was strictly limited to publicly accessible data. For data that could not be retrieved through automated methods, manual data collection techniques were employed. These manual procedures involved the researcher directly gathering information from eBay, ensuring both the accuracy of the data collected and adherence to ethical standards. This approach helped maintain data integrity while respecting eBay's terms of service and data privacy requirements.

This hybrid approach, blending automated data scraping with manual data collection, was specifically designed to meet the unique requirements of conducting research on eBay. It ensures compliance with platform rules while enhancing data accuracy and reliability. By balancing automation with manual oversight, the study upholds transparency, integrity, and ethical standards throughout the data collection process. This carefully designed strategy provided a robust foundation for the subsequent data analysis phases, ensuring that the study's findings are grounded in high-quality, reliable data.

3.4.2 Data Preparation

Data preparation is a critical phase in any data-driven research process, particularly in studies grounded in quantitative methodologies as the quality of the input data directly affects the validity, reliability, and interpretability of the analytical results. In this study, data preparation involves multiple steps—data cleaning, construction, data selection and data scaling—to ensure that the dataset is suitable for robust statistical and ML analyses.

3.4.2.1 Data Construction

The Data Construction section details the process of converting raw data into a format suitable for analysis. This involves cleaning and structuring the data to ensure its analytical readiness. In this study, the process includes two key steps: Data Transformation and Feature Engineering.

1) Data Transformation

Data transformation is a pre-processing step in statistical modelling and ML, particularly important when raw data violate underlying assumptions such as linearity, normality or homoscedasticity. Transformations aim to reshape the distribution of variables to enhance model performance, improve interpretability, and mitigate the influence of outliers or heteroscedastic effects. Depending on the characteristics of the data, transformation techniques can also reveal latent structure and relationships that would otherwise remain obscured.

This study employs two data transformation methods, logarithmic and Box-Cox, to address skewed distributions and unequal variances across features, enabling the application of parametric modelling techniques. Both methods serve to normalise the data and stabilise variance yet differ in flexibility and suitability depending on the scale and nature of variables.

- **Log Transformation**

Log-transformation is frequently applied when features span multiple orders of magnitude or exhibit strong right skewness. This method compresses the scale of large values while expanding smaller ones, thereby reducing the impact of outliers and stabilizing variance. The standard log-transformation is mathematically represented as:

$$\log(y_i)$$

However, when the dataset includes zero or negative values, a shifted log-transformation is applied to ensure that all transformed values remain positive:

$$\log(y_i + c)$$

In this equation, c is a constant chosen to shift the data such that the logarithm is defined for all values. Although the log-transformation is less flexible than the Box-Cox method, which adapts the transformation parameter λ to each feature, it remains a preferred choice for variables that inherently follow a multiplicative process.

- **Box-Cox Transformation**

The Box-Cox transformation offers a more adaptable approach by stabilizing variance and normalizing the distribution of features, which is particularly useful for reducing skewness. It is defined by the following expression:

$$y_i^{(\lambda)} = \begin{cases} \frac{y_i^\lambda - 1}{\lambda}, & \text{if } \lambda \neq 0 \\ \ln y_i, & \text{if } \lambda = 0 \end{cases}$$

where, y_i represents an individual observation, and λ is a parameter determined via maximum likelihood estimation for each feature. This approach ensures that the transformation optimally normalizes the data distribution, facilitating more robust and interpretable statistical analyses.

2) Sentiment Analysis (BERT)

To extract sentiment from unstructured textual data, the “Bert-base-multilingual-uncased-sentiment” model from the Hugging Face BERT family is employed. Developed by Devlin *et al.* (2019), BERT (Bidirectional Encoder Representations from Transformers) is known for its ability to generate deep bidirectional contextual representations by simultaneously considering both preceding and succeeding words in a sentence (Alaparthy and Mishra, 2021). This enables more accurate interpretation of sentiment-laden content within complex linguistic structures.

The “Bert-base-multilingual-uncased-sentiment” offers several distinct advantages: Its bidirectional architecture enables more accurate and context-sensitive interpretation of sentiment-laden content (Devlin *et al.*, 2019). As a pre-trained model, it can be deployed directly within analytical pipelines without requiring domain-specific fine-tuning, thereby reducing both computational cost and development time. Its multilingual capability enhances adaptability across diverse datasets, eliminating the need for language-specific modifications. Trained on a corpus exceeding 150,000 product reviews, it achieves an accuracy of 95% (± 1) for English reviews, aligning closely with human sentiment judgements. This renders it particularly effective for extracting sentiment signals from auction product descriptions. Its reliability and generalisability have been demonstrated in prior studies (e.g., Sousa *et al.*, 2019; Cao *et al.*, 2022), further supporting its applicability in consumer product analysis.

3.4.2.2 Feature Selection

This section outlines the methods used to identify and exclude variables of low importance in the analysis model, an essential step for enhancing performance in both regression and non-parametric methods (Maldonado *et al.*, 2015). High-dimensional models present several challenges, including difficulties in visualizing relationships between variables, increased computational demands, and greater statistical instability. Effective feature selection mitigates these issues by streamlining the dataset, reducing computational load, and improving overall model efficiency and stability.

Variables are divided into three relevance categories: unrelated, weakly related, and strongly related (John, Kohavi and Pfleger, 1994; Kohavi and John, 1997). Unrelated features are easily removed as they contribute little to the model's predictive power. Weakly related variables, however, require careful consideration as they may boost model accuracy but can also raise complexity and computational load, particularly in larger datasets or complex models.

Feature selection techniques are generally grouped into three categories: Wrapper, Filter, and Embedded methods, each with a unique approach to selecting relevant features.

- **Wrapper methods** (e.g., Recursive Feature Elimination and the Boruta algorithm) systemically evaluate subsets of variables to find combinations that maximise model performance. Though computationally intensive, wrapper methods often yield superior accuracy and are particularly suitable for complex datasets.
- **Filter methods** rely on statistical criteria (e.g., correlation coefficients, mutual information, or Chi-square scores) to rank variable relevance. These methods are computationally efficient and well-suited for preliminary analysis.

- **Embedded Methods** (e.g., Lasso regression or tree-based methods) integrate feature selection directly within the model-building process. These approaches are effective in regularising models and typically produce compact, high-performing feature sets.

This study adopts two widely used Wrapper techniques, Recursive Feature Elimination (RFE) and the Boruta algorithm, to evaluate and compare their effectiveness in identifying key variables. Additionally, SHAP values are used to further assess feature importance. SHAP values quantify each variable's contribution to the model's predictions, offering insights beyond mere importance ranking. By combining SHAP values with RFE and Boruta, this study improves the precision of feature selection, making the analysis model more robust. This hybrid approach allows for a comprehensive evaluation of variable importance, enhancing the overall reliability and generalizability of the model across varied datasets.

1) **Recursive Feature Elimination (RFE)**

RFE, introduced by Guyon *et al.*, (2002), is a robust wrapper-based feature selection method designed to identify the most relevant features by recursively removing the least important ones. The core idea is to iteratively train a model, rank features by importance, and eliminate the lowest-ranked features at each step until a predefined number of features remains.

The algorithm begins by training a model on the full set of variables and evaluating the contribution of each variable to the model's predictive performance. At each iteration, the least significant features are removed, producing a series of nested feature subsets, denoted as $S_1 > S_2 > \dots > S_s$. The model is retrained on each updated subset, and the process continues until the smallest subset containing the most informative features is identified. This iterative

procedure enhances both model performance and interpretability by retaining only the most critical predictors. However, removing multiple features simultaneously can lead to sub-optimal selections. To address this, Guyon *et al.* (2002) proposed a refined iterative strategy that carefully adjusts the feature elimination process to improve the quality of the resulting feature subset, especially when targeting minimal feature sets.

Process of Recursive Feature Elimination

The algorithm follows these steps, as detailed by Zhou *et al.*, (2021) and Habibi *et al.* (2023):

- 1) A ML model M is trained with the full feature set $X = \{x_1, x_2, \dots, x_m\}$.
- 2) Features are ranked according to their importance using SHAP values.
- 3) The least important feature x_k is removed from the feature set, producing a reduced subset: $X' = \{x_1, x_2, \dots, x_{k-1}, x_{k+1}, \dots, x_m\}$.
- 4) A new model M' is trained using the reduced feature set X' .
- 5) The performance of M' is evaluated using a predefined metric $P(M')$.
- 6) If the target number of features has not been reached, steps 2–5 are repeated. Otherwise, the algorithm terminates, returning the final feature subset.

2) Boruta

The Boruta algorithm is a robust wrapper-based feature selection method designed to identify all relevant features associated with the target variable (Kursa and Rudnicki, 2010). Unlike RFE, which focuses on selecting a minimal subset of the most predictive variables, Boruta aims to retain all features that contribute meaningfully to the prediction task, thereby reducing the risk of discarding weakly relevant but important variables (Kursa and Rudnicki, 2010).

Boruta leverages the randomness of the Random Forest algorithm to create a robust baseline for feature importance. The procedure begins by augmenting the original dataset with shadow features—shuffled copies of each original feature, thereby breaking any association with the target and introducing a random benchmark. In each iteration, the algorithm computes the importance of both original and shadow features using a standardised metric (Z-score):

$$z = \frac{x - \mu}{\sigma}$$

The maximum Z-score among the shadow features, referred to as ShadowMax, is used as the threshold. Features with Z-scores significantly exceeding ShadowMax are deemed important and retained, while those consistently below it are removed as irrelevant. This process is repeated across multiple iterations to ensure statistical robustness. Boruta’s conservative strategy is particularly advantageous in high-dimensional settings where overfitting and noise are prevalent. It has been widely adopted in bioinformatics, finance, and social science domains due to its ability to produce unbiased and comprehensive feature subsets (Kursa and Rudnicki, 2010; Degenhardt, Seifert and Szymczak, 2019).

3) Integrating SHAP with Boruta and RFE

Integrating SHAP with Boruta and RFE enhances both the reliability and interpretability of the feature selection process. This hybrid approach ensures that only features with demonstrable, statistically significant contributions to the target variable are retained, improving both model performance and transparency (Lundberg and Lee, 2017).

BorutaSHAP extends the Boruta algorithm by incorporating SHAP values in place of standard feature importance metrics derived from random forests. It evaluates the significance of each

feature by comparing its SHAP value to that of shadow features—random permutations of the original variables—thus enabling a rigorous and non-linear assessment of feature relevance (Kursa and Rudnicki, 2010). Features that consistently outperform these shadow counterparts are considered relevant and retained, while those failing to do so are excluded.

When integrated with RFE, which recursively removes the least important features through iterative model training, the combined process becomes both systematic and data driven. SHAP values enhance the explainability of RFE offering a clear explanation of each feature's contribution, thereby justifying the elimination or retention decisions (Habibi *et al.*, 2023). This integration also facilitates more accurate SHAP-based visualisations (e.g., SHAP dependence plots), by ensuring that only the most relevant features are used in the explanatory framework.

3.4.2.3 Data Scaling

Data scaling is an important preparation step designed to harmonize the range of feature values within a dataset and facilitating standardisation. This process mitigates the risk of variables with large numerical ranges disproportionately influencing analytical outcomes, not only in distance-based clustering but also in other ML algorithms sensitive to feature scale. The two scaler methods used in this thesis are shown below.

1) Standardisation

Standardisation, also known as z-score normalisation, is a method that centres the data by subtracting the mean and scales it by dividing by the standard deviation. This transformation results in a distribution with a mean of 0 and a standard deviation of 1:

$$x_{scaled} = \frac{x - \mu}{\sigma}$$

where x denotes the original value, μ is the mean of the feature, and σ is its standard deviation.

Standardisation is essential for algorithms that rely on the Euclidean distance metric, such as K-means clustering (Patel and Mehta, 2011), as it ensures that all features contribute equally to the analysis. By normalizing the scales, this method improves the accuracy and reliability of the results by reducing the risk of bias introduced by differing units of measurement.

2) Normalisation

Normalisation, particularly through MinMax scaling, adjusts each feature to a defined range, typically between 0 and 1. This transformation is expressed as:

$$X_{scaled} = \frac{X_i - \min(X)}{\max(X) - \min(X)}$$

where X_i represents an individual value, and $\min(X)$ and $\max(X)$ are the minimum and maximum values of the variable, respectively.

This rescaling preserves the intrinsic relationships within the data while ensuring that variables measured on different scales can be directly compared. Normalisation is especially useful for datasets with heterogeneous measurement units, as it reduces potential biases and provides a consistent basis for further analysis (Patro and Sahu, 2015).

3.4.3 Modelling

This section comprises several key steps: selecting appropriate algorithms, establishing testing protocols, constructing the models, and evaluating their predictive performance. While multiple techniques may be applicable for a given data mining task, certain methods have specific requirements regarding data structure or format. Consequently, it may be necessary to revisit the data preparation phase to ensure methodological compatibility. This study employs two primary analytical models—regression and clustering—and one supplementary model—classification. Each is aligned with one of the study’s three central research objectives and corresponding questions. Collectively, these models offer a structured framework for identifying and interpreting latent patterns and relationships within the data, thereby supporting a systematic investigation of the proposed research agenda.

3.4.3.1 Regression – Statistical Models

This section introduces the LR models employed to identify market signals from various stakeholders that influence the final auction prices of remanufactured products and to assess how these effects vary across different product condition levels. LR offers strong interpretability by clearly delineating the impact of individual predictors on the outcome variable. However, challenges such as overfitting and multicollinearity, particularly prevalent in high-dimensional datasets, can compromise model validity.

To address these limitations, the study incorporates regularisations, specifically Lasso and Ridge, alongside the baseline Ordinary Least Squares (OLS) model. These approaches apply penalty terms to stabilise coefficient estimates and enhance model generalisability. A

comparative analysis is conducted to evaluate the extent to which the regularised models improve predictive accuracy, robustness, and interpretability relative to OLS.

This approach provides a more comprehensive analysis of price determinants than previous studies, such as Van Nguyen *et al.* (2020), who examined customer demand using only OLS within the framework of LR. By incorporating regularisation techniques especially Lasso for variable selection and Ridge for coefficient stabilisation, this study address key limitations of traditional models. The resulting models are more robust, generalisable, and interpretable models, yielding deeper insights into the pricing dynamics of remanufactured electronics in online auction markets.

The following sections provide a detailed discussion of each LR model used in this study, outlining their theoretical foundations, implementation procedures and the characteristics. This comprehensive modelling framework ensures methodological robustness and contributes to the study's overarching aim of generating rigorous insights into price formation mechanisms in the online secondary market for remanufactured products.

1) Ordinary Least Square (OLS)

Ordinary Least Squares (OLS) regression is a fundamental statistical method used to examine the relationship between a dependent variable and one or more independent variables. It is widely valued for its simplicity, interpretability, and efficiency in estimating linear relationships. OLS enables multivariate regression, allowing multiple explanatory variables to be analysed simultaneously to determine their combined effect on the dependent variable.

Mathematical Foundations

The OLS regression model is mathematically defined by the following linear equation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$$

where Y represents the dependent variable, β_0 denotes the intercept, β_j (for $j = 1, 2, \dots, n$) are the coefficients or weights for each independent variable X_j , ϵ is the error term, representing the difference between the predicted and actual values.

OLS estimates the optimal coefficients β_j by minimising the sum of the squared errors (SSE) between the observed values $y^{(i)}$ and the predicted values $\hat{y}^{(i)}$, as follows:

$$\hat{\beta} = \arg \min_{\beta_0, \dots, \beta_p} \sum_{i=1}^n \left(y^{(i)} - \left(\beta_0 + \sum_{j=1}^p \beta_j x_j^{(i)} \right) \right)^2$$

This minimization ensures that the estimated coefficients result in the best possible linear fit to the given data, adhering to the least-squares criterion.

Advantages and Disadvantages

A key advantage of OLS regression is its ability to incorporate multiple explanatory variables, making it particularly useful for analysing complex relationships within structured datasets. However, OLS is subject to significant limitations, particularly in high-dimensional datasets or when multicollinearity exists among independent variables. Under such conditions, coefficient estimates may become unstable, increasing the risk of overfitting and undermining the reliability and interpretability of the model's outputs.

2) Lasso Regression

Lasso (Least Absolute Shrinkage and Selection Operator) regression is an advanced modelling technique that applies L1 regularization, effectively shrinking the coefficients of less significant variables to zero. This characteristic enables automatic variable selection, making Lasso particularly beneficial for high-dimensional datasets with numerous predictors, some of which may be redundant or irrelevant (Tibshirani, 1996). By isolating the most relevant predictors, Lasso creates simpler, more interpretable models while preserving predictive accuracy.

Mathematical Foundations

The mathematical formulation of Lasso regression is calculated as follows:

$$\hat{\beta} = \arg \min_{\beta_0, \dots, \beta_p} \sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^p |\beta_j|$$

where y_i is the observed outcome, β_0 is the intercept, x_{ij} are the predictors, β_j are the regression coefficients, and λ is the regularization parameter controlling the penalty strength.

Advantages and Disadvantages

Lasso regression offers several advantages,

- **Automatic Variable Selection:** By applying an L1 regularisation penalty, Lasso shrinks some regression coefficients to exactly zero, effectively selecting only the most relevant predictors (Tibshirani, 1996; Zou and Hastie, 2005).
- **Overfitting Reduction:** Lasso helps prevent overfitting by introducing bias that reduces variance, thereby improving predictive performance on unseen data (Hastie, Tibshirani, and Friedman, 2009).

- **Improved Model Interpretability:** By retaining only the most relevant variables, Lasso enhances model transparency and facilitates clearer interpretation (Hastie, Tibshirani, and Friedman, 2009).

However, Lasso also has limitations.

- **Instability with Correlated Predictors:** When predictors are highly correlated, Lasso tends to select one and discard the others arbitrarily, potentially ignoring shared explanatory power.
- **Bias Introduction:** The shrinkage process introduces bias in the coefficient estimates, which may reduce in-sample accuracy compared to unregularized models.
- **Sensitivity to Parameter:** Model performance is highly dependent on the choice of the regularisation parameter. Suboptimal selection can lead to underfitting or overfitting.

3) Ridge Regression

Ridge regression, introduced by Hoerl and Kennard (1970), is an advanced regression technique designed to address multicollinearity by applying an L2 penalty to the regression coefficients. Unlike traditional OLS, which may yield unstable estimates when independent variables are highly correlated, Ridge regression shrinks coefficients toward zero while ensuring that no variable is eliminated from the model. This approach helps retain all relevant predictors, making Ridge particularly effective for complex datasets with numerous interrelated features.

Mathematical Foundations

The mathematical formulation of Ridge regression is:

$$\hat{\beta} = \arg \min_{\beta_0, \dots, \beta_p} \sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^p \beta_j^2$$

where λ serves as the regularization parameter that controls the penalty. The larger the λ , the more the coefficients are shrunk, but none are reduced to zero, ensuring all variables are kept.

Advantages and Disadvantages

Ridge regression is effective in high-dimensional settings and when multicollinearity is present.

- **Handles Multicollinearity Effectively:** Ridge regression mitigates multicollinearity by shrinking coefficient estimates, which stabilises the model when predictors are highly correlated (Hoerl and Kennard, 1970).
- **Retains All Predictors:** Unlike Lasso, Ridge does not set coefficients to zero. This makes it suitable in contexts where all variables are expected to carry meaningful, if small, explanatory power (Hastie, Tibshirani and Friedman, 2009).
- **Improves Generalisation through Bias–Variance Trade-off:** By accepting a small amount of bias, Ridge substantially reduces variance, leading to more reliable predictions on new data (James *et al.*, 2013).
- **Performs Well in High-Dimensional Settings:** Particularly effective when the number of predictors is large relative to the number of observations, a common issue in marketing or behavioural data (Friedman, Hastie, and Tibshirani, 2010).

Ridge regression is less suitable when interpretability or variable selection is a key objective.

- **No Feature Selection:** Ridge retains all variables with non-zero coefficients, including irrelevant ones, which may hinder interpretability (James *et al.*, 2013).

- **Reduced Model Sparsity:** Unlike Lasso, Ridge cannot produce sparse models. This makes it less suitable when model simplification or feature reduction is a primary goal.
- **Sensitive to Regularisation Parameter (λ):** Model performance is highly dependent on the appropriate tuning of λ , which typically requires cross-validation for optimal selection (Friedman, Hastie, and Tibshirani, 2010).

3.4.3.2 Regression – Machine Learning Models

Machine Learning (ML) models are well-suited for capturing complex, non-linear relationships that traditional statistical approaches may fail to detect (LeCun, Bengio and Hinton, 2015). Their ability to analyse large, high-dimensional datasets makes ML models particularly effective for capturing the nuanced effects of market signals and remanufactured product conditions on auction outcomes—phenomena that do not follow simple linearity (Van Nguyen *et al.*, 2020). Unlike LR, which relies on fixed functional forms and additive assumptions, ML models adapt flexibly to complex data structures, making them especially suitable for exploring non-linear interactions inherent in price variations across condition levels.

Despite their strengths in predictive accuracy, ML models face challenges regarding interpretability and the risk of overfitting. To mitigate these limitations, this study incorporates a tree-based regression model, Classification and Regression Trees (CART), which offers a balance between interpretability and modelling flexibility. Importantly, CART serves as the foundational model upon which two ensemble methods, Random Forest (RF) and Extreme Gradient Boosting (XGBoost), are built. This structure mirrors the study's LR strategy, where OLS forms the baseline and Ridge and Lasso are introduced to address its limitations.

Similarly, RF and XGBoost extend CART's core principles by aggregating multiple decision trees, significantly enhancing predictive accuracy, reducing variance, and increasing robustness in large, complex datasets. These ensemble models also provide more stable and reliable estimates of feature importance, supporting deeper insights into auction pricing dynamics. The following sections outline the theoretical foundations, implementation procedures, and practical relevance of each model to the study's research questions.

1) Classification and Regression Trees (CART)

Decision Tree (DT) method is a powerful and interpretable ML algorithms that partition data into increasingly homogeneous subsets using hierarchical rules. This structure enables them to model complex relationships while maintaining transparency and ease of interpretation.

Van Nguyen *et al.* (2020) employed both CART and M5 models to compare the performance of decision tree-based algorithms. CART constructs binary trees using impurity-based criteria, such as mean squared error (MSE) for regression tasks, yielding models that are both interpretable and effective across diverse data structures (Breiman *et al.*, 1984). In contrast, the M5 model incorporates LR at the terminal nodes, allowing for more precise local approximations in scenarios with piecewise linear relationships. This hybrid structure enhances predictive accuracy by fitting LR models within each leaf, offering a nuanced approach to regression problems.

However, the present study focuses exclusively on CART, owing to its greater interpretability, computational efficiency, and established capacity to model non-linear feature interactions. While M5 offers advantages in certain regression contexts, it was excluded from this analysis

due to its architectural and methodological divergence from ensemble-based learning. Since this study aims to evaluate generalisation performance within an ensemble framework, methods that align with and extend CART's structure, namely RF and XGBoost, were prioritised. These ensemble models build on CART's foundations by aggregating multiple trees to boost predictive accuracy, reduce overfitting, and enhance robustness, particularly in high-dimensional and complex data environments.

Mathematical Foundations

For regression tasks, let the training data consist of feature vectors $X_i \in \mathbb{R}^n$ and corresponding target values $y_i \in \mathbb{R}$. A decision tree recursively partitions the feature space to minimise the variability of the target values within each resulting region.

At each node m , with data Q_m comprising n_m samples, a candidate split $\theta = (j, t_m)$ divides the data based on threshold t_m for feature j into:

$$Q_m^{left}(\theta) = \{(x, y) | x_j \leq t_m\}, Q_m^{right}(\theta) = Q_m \setminus Q_m^{left}(\theta)$$

The quality of a split is assessed using an impurity function $H(\cdot)$, typically the Mean Squared Error (MSE) in regression. The impurity after the split is:

$$G(Q_m, \theta) = \frac{n_m^{left}}{n_m} H(Q_m^{left}(\theta)) + \frac{n_m^{right}}{n_m} H(Q_m^{right}(\theta))$$

where n_m^{left} and n_m^{right} are the number of samples in each child node. The optimal split θ^* is then determined by:

$$\theta^* = \arg \min_{\theta} G(Q_m, \theta)$$

The recursive partitioning continues until one of the predefined stopping criteria is met: the tree reaches a maximum depth, the number of samples in a node falls below a set threshold, or the node contains a single sample ($n_m = 1$). This greedy, top-down approach ensures that each split maximally reduces prediction error at that stage.

Advantages and Disadvantages

CART offers several compelling advantages that make them particularly useful for structured prediction tasks, including auction price modelling:

- **Non-linear Modelling Capability:** CART effectively captures non-linear relationships and complex feature interactions by recursively partitioning the data based on input variable thresholds, which is especially useful when auction pricing mechanisms deviate from linear assumptions (Breiman *et al.*, 1984).
- **Simplicity and Interpretability:** The binary tree structure yields easily interpretable decision rules, providing transparency in how predictions are made. This makes CART particularly appealing in contexts where explainability is important, such as pricing analytics and policy decision-making (Breiman *et al.*, 1984).
- **Versatility with Data Types:** CART handles both categorical and continuous predictors without requiring extensive preprocessing, making it suitable for mixed-type datasets frequently encountered in auction data.
- **Adaptability to Regression and Classification:** Unlike some other DT algorithms, CART naturally supports both regression and classification tasks, making it flexible for varied applications, including predicting continuous auction outcomes (Quinlan, 1986).

However, despite these strengths, CART is also associated with several important limitations:

- **Risk of Overfitting:** One of the major drawbacks of CART is its propensity to overfit the training data, particularly when deep trees are allowed to grow without constraint. Overfitted trees may capture noise instead of meaningful patterns, reducing generalisability to new data (Breiman *et al.*, 1984).
- **Instability to Data Perturbations:** CART is sensitive to small changes in the training set, which can result in large variations in tree structure and predictions. This lack of robustness makes the CART model less reliable in production settings (Podgorelec *et al.*, 2002).
- **Suboptimal Splitting and Early Stopping:** The greedy nature of the splitting algorithm may lead to locally optimal decisions, and without adequate tuning (e.g., through pruning, depth constraints, or minimum sample thresholds), trees may stop growing prematurely or grow excessively (Podgorelec *et al.*, 2002; Hastie, Tibshirani and Friedman, 2009).

For these reasons, while CART remains a foundational and interpretable modelling technique, its predictive limitations are often addressed through ensemble extensions such as Random Forest and XGBoost, which build upon CART's core structure while mitigating its weaknesses.

2) Random Forest (RF)

Random Forest (RF) is an ensemble learning method that improves predictive accuracy and model stability by aggregating the outputs of multiple decision trees built using the CART algorithm (Breiman, 2001). It introduces randomness through two mechanisms: bagging, where each tree is trained on a bootstrap sample of the data, and random feature selection, which limits the number of predictors considered at each split (Ho, 1995). This dual randomisation promotes model diversity and reduces overfitting. RF is particularly effective in high-dimensional, noisy datasets and accommodates both categorical and continuous variables with minimal

preprocessing. Its capacity to estimate feature importance also enhances model interpretability, making it well-suited for analysing complex auction environments with heterogeneous inputs.

This study employs RF as a bagging-based benchmark ensemble model alongside the boosting-based XGBoost to assess the predictive power of market signals on auction prices for remanufactured products and to compare the effects across different product condition levels. With its strength in predictive performance and handling non-linear interactions, RF contributes to understanding price dynamics and benchmarking against other regression models.

Mathematical Foundations

In regression tasks, RF optimises predictive performance by minimising the Mean Squared Error (MSE) at each split within a tree. The MSE impurity measure is defined as:

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y})^2$$

where y_i denotes the true value for the i -th sample, $\hat{y}$ represents the predicted value (typically the mean of the target values in that node), and N is the number of samples in the node.

Once the ensemble is trained, RF makes predictions by averaging the outputs from all individual decision trees:

$$\hat{y} = \frac{1}{B} \sum_{i=1}^B T_i(x)$$

where $T_i(x)$ is the prediction of the i -th tree for input x , and B is the total number of trees in the forest.

This averaging mechanism effectively reduces model variance and enhances generalisation, making RF particularly robust and reliable in high-variance regression scenarios.

Bootstrap Aggregating (Bagging)

RF improves predictive performance through bagging, a technique in which multiple decision trees are trained independently on different bootstrap samples—random subsets of the training data drawn with replacement (Breiman, 2001). For regression tasks, the final output is computed by averaging all tree predictions; for classification, majority voting determines the outcome (Hastie, Tibshirani, and Friedman, 2009). This aggregation reduces model variance and enhances stability, as each tree is exposed to a distinct version of the data, limiting sensitivity to noise or outliers. Moreover, by integrating multiple weak learners that each offer a partial view of the dataset, bagging mitigates the overfitting commonly associated with individual decision trees. The resulting ensemble smooths out extreme predictions and delivers more reliable generalisation to unseen data, making RF particularly effective in complex, noisy, or high-dimensional environments.

Random Feature Selection

Beyond bagging, RF enhances model diversity through random feature selection at each node split. Instead of evaluating all available predictors, the algorithm randomly selects a subset of features from which the best split is chosen (Breiman, 2001). This process introduces additional randomness that reduces the risk of over-reliance on dominant or highly correlated variables, which is especially valuable in high-dimensional datasets where many predictors may be weakly informative or redundant. By compelling each tree to consider different feature subsets,

RF fosters complementary learning across the ensemble and enables the model to capture a wider array of patterns and interactions within the data. Together, bagging and random feature selection enable Random Forest to generalise well, maintain predictive stability, and effectively manage complex, high-dimensional datasets.

Advantages and Disadvantages

RF offers several compelling advantages that make it a widely adopted ML algorithm:

- **High Predictive Accuracy:** RF enhances model stability and accuracy by averaging predictions across multiple decision trees, effectively reducing variance compared to single-tree models (Breiman, 2001). This ensemble strategy is particularly effective in complex, non-linear, and high-dimensional environments.
- **Robustness to Overfitting:** By incorporating both bagging and random feature selection, RF mitigates the risk of overfitting often associated with individual trees. This design enables the model to generalise well, even in the noisy or imbalanced data (Ho, 1995).
- **Versatility with High-Dimension and Mixed-Type Data:** RF handles both numerical and categorical data with minimal preprocessing. It remains effective even when many features are weakly informative or redundant (Genuer, Poggi and Tuleau-Malot, 2010).
- **Feature Importance Estimation:** The algorithm provides built-in measures of feature importance, facilitating model interpretability and supporting informed variable selection in high-dimensional settings (Hastie, Tibshirani and Friedman, 2009; Strobl et al., 2007).
- **Tolerance to Outliers and Missing Data:** The tree-based structure allows RF to manage outliers and incomplete data without extensive preprocessing, enhancing robustness across diverse data conditions.
- **Parallelisability:** RF is well-suited for parallel processing, as individual trees are trained

independently. This characteristic significantly improves training efficiency on modern computing architectures.

Despite its strengths, RF has several limitations:

- **Limited Interpretability:** While aggregate feature importance is available, the ensemble nature of RF obscures the internal logic behind individual predictions, limiting transparency (Strobl et al., 2007)
- **High Computational Demand:** Training and inference can be computationally expensive, especially when large forests are built with deep trees, leading to high memory and processing costs (Oshiro, Perez and Baranauskas, 2012).
- **Bias in Feature Importance Metrics:** RF's default Gini-based importance measure can exhibit bias toward variables with more levels or high cardinality, potentially distorting interpretability (Strobl et al., 2007).
- **Unsuitability for Real-Time Applications:** The ensemble structure can slow down prediction speed, making RF less ideal for latency-sensitive or real-time decision-making.

3) Extreme Gradient Boosting (XGBoost)

Extreme Gradient Boosting (XGBoost) is a high-performance ensemble learning algorithm designed for accuracy, scalability, and computational efficiency. As an advanced implementation of gradient boosting, XGBoost builds decision trees sequentially, where each tree is trained to correct the residual errors of its predecessors, enabling the model to capture complex, non-linear relationships in the data (Friedman, 2001). XGBoost incorporates multiple algorithmic innovations that distinguish it from traditional boosting methods. These include second-order gradient approximation for more precise optimisation, regularisation terms (L1 and L2) to control model complexity, shrinkage to prevent overfitting, and column subsampling

to enhance diversity and speed. These mechanisms make XGBoost particularly effective in high-dimensional, sparse, or imbalanced datasets.

In this study, XGBoost is employed alongside the bagging-based Random Forest as a boosting-based benchmark ensemble model. It is used to evaluate the predictive power of market signals in determining auction prices for remanufactured products and to compare these effects across various product condition levels. Due to its ability to model complex feature interactions and maintain robustness under noisy conditions, XGBoost plays a key role in analysing price variation and benchmarking model performance against alternative regression techniques.

Mathematical Foundations

The objective function in XGBoost combines a loss function with a regularization term to balance model accuracy and complexity. It is defined as follows:

$$\text{Obj}(\theta) = \sum_{i=1}^n L(y_i, \hat{y}) + \sum_{k=1}^K \Omega(f_k)$$

where $L(y_i, \hat{y})$ denotes the loss function, which measures the difference between the true label y_i and the predicted values $\hat{y}_i$. The term $\Omega(f_k)$ represents the regularization penalty on the complexity of the individual trees f_k , and K is the total number of trees in the ensemble. This formulation encourages the model to achieve a trade-off between minimising prediction error and avoiding overfitting through regularisation.

To optimise this objective efficiently, XGBoost applies a second-order Taylor approximation to the loss function around the current prediction at each iteration t . For each training instance i , the first and second derivatives of the loss function with respect to the prediction are:

$$\text{Gradient (First Derivative): } g_i = \frac{\partial L(y_i, \hat{y}_i^{t-1})}{\partial \hat{y}_i^{t-1}}$$

$$\text{Hessian (Second Derivative): } h_i = \frac{\partial^2 L(y_i, \hat{y}_i^{t-1})}{(\partial \hat{y}_i^{t-1})^2}$$

These derivatives inform the optimisation direction and step size, allowing the model to iteratively update its predictions in a more informed and efficient manner.

Tree Structure Optimization

At each boosting iteration, XGBoost constructs a new regression tree f_t to minimise the following regularised objective, derived from the Taylor-expanded loss:

$$Obj^{(t)} = \sum_{i=1}^n \left[g_i f_t(x_i) + \frac{1}{2} h_i f_t(x_i)^2 \right] + \Omega(f_t)$$

where, $f_t(x_i)$ represents the prediction of the new tree for instance x_i and $\Omega(f_t)$ penalises the complexity of this tree, typically measured in terms of the number of leaves and their associated weights.

This formulation allows the algorithm to optimise the structure of each tree not only to fit the residuals but also to maintain model simplicity and generalisability. By integrating gradient-based optimisation with regularisation at each step, XGBoost ensures efficient training and robust predictive performance, particularly in complex, high-dimensional settings.

Boosting

Boosting is the core mechanism that distinguishes XGBoost from other ensemble learning techniques such as RF. Unlike bagging methods, which train multiple trees independently and

in parallel, boosting builds trees sequentially, where each successive tree aims to correct the residual errors of its predecessors (Friedman, 2001). This sequential dependency enables the model to progressively focus on difficult-to-predict instances, thereby refining its predictions with each iteration. The objective is to minimise a predefined loss function that quantifies the discrepancy between predicted and true values, resulting in a highly accurate and robust ensemble model.

Regularization in XGBoost

A critical innovation in XGBoost is its incorporation of regularisation directly into the learning objective, which helps control model complexity and prevents overfitting. The regularisation term is defined as:

$$\Omega(f) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2$$

where, T represents the number of leaves in a tree, w_j is the weight associated with the j -th leaf, γ penalises the number of leaves to control model complexity, and λ discourages excessively large leaf weights to prevent any single node from dominating the prediction.

XGBoost supports both L1 and L2 regularisations, offering flexibility in balancing model sparsity and generalisation. These regularisations ensure that the resulting models are not only accurate but also resistant to overfitting, particularly in high-dimensional or noisy data.

Advantages and Disadvantages

XGBoost offers several key advantages that make it one of the most widely used ML algorithms for structured data:

- **High Predictive Accuracy:** XGBoost delivers state-of-the-art performance across a wide range of regression and classification tasks, owing to its gradient boosting architecture and capacity to capture complex, non-linear relationships (Chen and Guestrin, 2016).
- **Regularisation for Overfitting Control:** Unlike traditional boosting algorithms, XGBoost incorporates both L1 and L2 regularisation terms directly into the objective function, providing effective control over model complexity and enhancing generalisability (Friedman, 2001).
- **Scalability and Computational Efficiency:** The algorithm supports parallelised tree construction, out-of-core computation, and GPU acceleration, enabling fast training even on large-scale datasets with high dimensionality (Chen and Guestrin, 2016).
- **Robustness to Noisy and Missing Data:** XGBoost can handle missing values internally by learning optimal default directions in tree splits and is relatively resilient to noise due to its regularisation and boosting strategy.
- **Comprehensive Feature Handling:** The algorithm accommodates both continuous and categorical variables (after encoding) and provides built-in feature importance metrics that support interpretability and variable selection (Lundberg and Lee, 2017).
- **Customisation and Flexibility:** XGBoost offers extensive hyperparameter tuning options, including learning rate, tree depth, subsample ratios, and column sampling, allowing precise control over model training dynamics.

Despite its strengths, XGBoost has several limitations:

- **Reduced Interpretability:** As an ensemble of many boosted trees, the internal logic of individual predictions is difficult to trace, making model interpretation non-trivial without the aid of post-hoc explainability tools such as SHAP (Lundberg and Lee, 2017).
- **Complex Hyperparameter Tuning:** Achieving optimal performance often requires extensive tuning across multiple parameters, which can be time-consuming and computationally intensive.
- **Inference Overhead:** Prediction times may be slower compared to simpler models, especially in real-time applications, due to the cumulative nature of boosted trees.

3.4.3.3 Clustering

Clustering is a fundamental unsupervised ML technique that groups data points into clusters based on their intrinsic similarities. Unlike supervised learning methods such as classification or regression, clustering does not rely on predefined labels. Instead, its primary objective is to divide a dataset into distinct groups in which data points within the same cluster are highly similar to one another, while those in different clusters are dissimilar. This capability makes clustering a powerful tool for uncovering hidden patterns in data and is widely applied in tasks such as exploratory data analysis, pattern recognition, and anomaly detection.

Clustering algorithms can be broadly categorised into four main types, each suited to different data characteristics and analysis goals.

- **Distance-based methods** (e.g., K-means) assign data points to a fixed number of non-overlapping clusters based on similarity, typically using distance metrics.

- **Hierarchical methods** (e.g., agglomerative clustering) create a tree-like structure of nested clusters, allowing multi-level insights into data groupings.
- **Density-based methods** (e.g., DBSCAN) identify clusters as regions of high point density, effectively detecting noise and irregularly shaped clusters.
- **Model-based methods** (e.g., Gaussian Mixture Models) assume that data are generated from a mixture of distributions and use statistical inference to model the cluster structure.

Aligned with the third research objective—to explore bidder heterogeneity in remanufactured product auctions—clustering provides an effective means of identifying diverse bidding strategies that emerge from behavioural patterns in the data. By grouping bidders with similar activity profiles, clustering facilitates a nuanced understanding of strategic variation within the auction environment. These methods collectively offer a robust toolkit for uncovering latent bidder segments and evaluating the strategic diversity in remanufactured product auctions.

The following section details the K-means clustering technique adopted in this study, along with Principal Component Analysis (PCA), which was applied as a prerequisite dimensionality reduction method. PCA was incorporated during the modelling phase to reduce feature dimensionality prior to clustering, thereby enhancing the identification of latent structures and improving the visual interpretability of cluster distributions. This combination enables more efficient and meaningful segmentation, particularly in high-dimensional datasets.

1) Principal Component Analysis (PCA)

PCA is a widely used dimensionality reduction technique that addresses key challenges in clustering high-dimensional data, particularly the curse of dimensionality, which can lead to increased computational burden, overfitting, and degraded model performance (Hinneburg and Keim, 1999). PCA mitigates these issues by transforming correlated variables into a smaller set of uncorrelated principal components, ordered by the amount of variance they capture (Jolliffe, 2002). The first few components typically retain most of the dataset's variability, thereby preserving essential information while discarding noise and redundancy.

This transformation not only improves computational efficiency but also enhances the effectiveness of clustering algorithms, such as K-means, by enabling them to operate in a more compact and information-rich feature space. Ding and He (2004) analytically demonstrated that applying PCA prior to K-means aligns the subspace projection with the optimal cluster structure, improving both cluster separability and interpretability. By working in a reduced-dimensional space, clustering algorithms are better equipped to detect meaningful groupings and are less influenced by irrelevant or weakly informative variables.

Furthermore, PCA facilitates the visualisation of complex, high-dimensional data by projecting it onto two or three principal components. This projection simplifies the interpretation of clustering outcomes, supports post-hoc explanatory analysis (e.g. feature attribution or cluster profiling), and enhances communication with non-technical audiences. As noted in **Table 2.5**, PCA is frequently paired with K-means in explainable clustering studies due to its dual benefits of improved model performance and interpretability.

In summary, PCA enables clustering models to uncover latent structures in a refined, lower-dimensional representation of the data. Its integration with K-means is both empirically validated and theoretically grounded, making it a standard and effective component in explainable unsupervised learning workflows.

Optimal Number of Principal Components

Determining the optimal number of principal components is a critical step in PCA, as it directly impacts the trade-off between dimensionality reduction and information retention. To guide this selection, three widely adopted criteria are commonly used: the Eigenvalue Criterion, the Cumulative Explained Variance (CEV) threshold, and the Scree Plot method (Jolliffe, 2002; Boehmke and Greenwell, 2020). Applying these methods either individually or in combination enables practitioners to retain only the most informative components, thereby improving model interpretability, reducing computational burden, and enhancing overall analytical performance. This structured approach ensures that PCA remains both statistically rigorous and practically effective when handling high-dimensional datasets.

- **Eigenvalue Criterion**

The eigenvalue criterion, commonly referred to as the Kaiser rule (Kaiser, 1960), offers a practical guideline for selecting principal components in Principal Component Analysis (PCA). Under this rule, only components with eigenvalues greater than 1 are retained. Since an eigenvalue represents the amount of variance explained by a principal component, a value exceeding 1 implies that the component captures more variance than any single original variable and is thus considered informative. Conversely, components with eigenvalues less than 1 explain less variance than an individual observed variable and are typically discarded.

This criterion provides a simple yet effective approach to dimensionality reduction by ensuring that only the most variance-contributing components are retained for interpretation (Jolliffe, 2002). It is particularly useful in exploratory data analysis, where ease of implementation and interpretability are essential. At the core of PCA is the eigenvalue decomposition of the data's covariance matrix. Given a data matrix X with n observations and p variables, the covariance matrix Σ is computed as:

$$\Sigma = \frac{1}{n-1} X^T X$$

PCA then involves solving the eigenvalue equation:

$$\Sigma v = \lambda v$$

where, λ is the eigenvalue associated with the principal component, quantifying its contribution to the total variance, and v is the corresponding eigenvector, indicating the direction of that component in the feature space.

In practice, applying the Kaiser rule helps retain only those components that meaningfully summarise the variability in the data, thereby enhancing interpretability while avoiding unnecessary complexity.

- **Cumulative Explained Variance (CEV)**

Cumulative Explained Variance (CEV) is a widely adopted criterion for determining the optimal number of principal components to retain in dimensionality reduction tasks. This approach involves selecting the smallest number of components k such that they collectively

explain a predetermined proportion of the total variance in the dataset, typically ranging from 70% to 90% (Jolliffe, 2002; Jolliffe and Cadima, 2016). The choice of threshold reflects a trade-off between preserving sufficient data structure and minimising redundancy or noise. For example, a 70% threshold captures the dominant trends in the data with fewer dimensions, while a 90% threshold retains more components to preserve finer-grained variance at the expense of higher dimensionality.

Mathematically, Cumulative Explained Variance is computed as:

$$\text{Cumulative Explained Variance} = \frac{\sum_{i=1}^k \lambda_i}{\sum_{i=1}^p \lambda_i}$$

where λ_i represents the eigenvalue of the i -th component, k is the number of components retained, and p is the total number of principal components.

This method provides a quantitative basis for balancing the reduction of dimensionality with the retention of critical variance in the data. A threshold that is set too low may lead to information loss and impaired model performance, whereas an excessively high threshold may retain superfluous components, undermining the efficiency gains of dimensionality reduction.

- **Scree plot**

Complementing quantitative methods such as the cumulative explained variance criterion, the Scree plot provides a visual approach for determining the optimal number of principal components. In this plot, eigenvalues are arranged in descending order and plotted against the component index. The resulting curve typically exhibits a steep decline followed by a gradual flattening. The elbow point, where the rate of decrease transitions from sharp to gradual,

indicates the number of components that account for the most substantial variance (Boehmke and Greenwell, 2020). Components preceding this elbow are regarded as the primary contributors to the data's structure, while those beyond it contribute minimally and may introduce redundancy. The Scree plot is particularly useful when the ideal number of components is not evident from numerical criteria alone, offering an intuitive means of identifying the point of diminishing returns in variance explanation.

2) K-means Clustering

K-means clustering is a widely adopted unsupervised learning algorithm that excels in uncovering latent structures within large datasets. Its primary strength lies in its simplicity, computational efficiency, and ability to produce clearly defined, non-overlapping clusters based on proximity in the feature space (MacQueen, 1967; Jain, 2010). By grouping data points around centroid-based representations, K-means is particularly effective for identifying behavioural patterns and segmenting entities with shared characteristics. These properties make it well-suited for auction data analysis, where understanding heterogeneity among bidders is essential for interpreting strategy variation and market dynamics.

In this study, K-means clustering was selected for investigating bidder heterogeneity in remanufactured product auctions, as addressed in Research Objective 3. This choice is supported by prior literature: as summarised in **Table 2.3** (Section 2.4.3), most existing studies on bidder heterogeneity have employed K-means clustering. Furthermore, as shown in **Table 2.5**, these studies commonly applied PCA as a dimensionality reduction technique in conjunction with K-means. Benchmarking against this established framework, the present study

also considered an alternative approach, DBSCAN, for comparison, as discussed in Section 6.4, thereby providing a justified basis for model selection.

K-means Clustering Process

The algorithm follows an iterative refinement process, which can be summarized in four steps:

1. **Initialization:** The algorithm starts by randomly selecting k initial centroids, denoted as $\mu_1, \mu_2, \dots, \mu_k$. This random initialisation provides the starting point for the clustering.
2. **Assignment:** Each data point x_i is assigned to the nearest centroid based on the Euclidean distance. This is mathematically expressed as:

$$j = \arg \min_j \|x_i - \mu_j\|^2$$

In this step, x_i is assigned to the cluster corresponding to centroid μ_j that minimizes the squared distance. This step ensures that each data point is grouped with the most similar cluster centre.

3. **Update:** After the assignment step, the centroids are recalculated by taking the mean of all data points within each cluster C_j .

$$\mu_j = \frac{1}{|C_j|} \sum_{x_i \in C_j} x_i$$

Here, $|C_j|$ represents the number of data points in cluster j . This step updates the position of each centroid to better reflect the current cluster composition.

4. **Repeat:** The assignment and update steps are repeated iteratively until the centroids stabilize—meaning there is no notable change in their positions between successive iterations—or until a predetermined number of iterations is reached.

This iterative process converges to a solution where the clustering is optimized according to the chosen objective function. By continuously refining the clusters through these steps, K-means effectively minimizes the within-cluster sum of squares, yielding clusters that are both compact and well-separated.

Advantages and Disadvantages

K-means clustering offers several advantages that contribute to its widespread adoption in unsupervised learning, especially for large-scale data analysis:

- **Computational Efficiency:** K-means is highly efficient in terms of time and memory complexity. It scales well to large datasets and high-dimensional spaces, making it suitable for real-time applications and big data contexts (Jain, 2010; Morissette and Chartier, 2013).
- **Simplicity and Interpretability:** The algorithm is straightforward to implement and yields intuitive results by grouping similar observations based on proximity to centroids. This simplicity facilitates quick exploratory analysis and visual interpretation.
- **Integration with Dimensionality Reduction:** When combined with techniques such as PCA, K-means can more effectively identify latent patterns and enhance cluster separability in high-dimensional data (Ding and He, 2004).

Despite these strengths, K-means also presents several notable limitations:

- **Assumption of Spherical Clusters:** The algorithm assumes that clusters are isotropic and of similar size and density, which can lead to suboptimal results in real-world data where cluster shapes and distributions vary (Steinley, 2006).
- **Sensitivity to Initialization:** The final clustering outcome is influenced by the initial placement of centroids. Poor initialization may lead to convergence at local optima,

compromising clustering accuracy (Arthur and Vassilvitskii, 2007).

- **Vulnerability to Outliers:** Since K-means minimises squared distances, it is highly sensitive to outliers and noisy data points, which can distort centroid placement and degrade performance.
- **Fixed Number of Clusters:** K-means requires the number of clusters (k) to be predefined, which is often nontrivial to estimate accurately and can affect the quality of the resulting partitions (Jain, 2010).

For datasets that do not meet the assumptions of K-means, alternative clustering methods, such as DBSCAN for arbitrary-shaped clusters or Gaussian Mixture Models for probabilistic partitioning, may be more appropriate.

3.4.3.4 Classification

Aligned with Research Objective 3, which aims to enhance the interpretability of unsupervised learning outcomes, this study employs a post-hoc classification framework to explain the clustering results. After the clustering procedure, the assigned cluster labels are repurposed as target variables, effectively transforming the unsupervised problem into a supervised multi-class classification task. This enables the use of explainable classification models to assess input features most significantly influence cluster assignment.

By training a classifier on the original feature space to predict the derived cluster labels, feature importance metrics can be extracted. These metrics provide insights into the distinguishing characteristics of each cluster and support a more transparent, data-driven interpretation of the

clustering structure. This approach not only enhances model explainability but also bridges the gap between exploratory clustering and actionable insights.

1) XGBoost Classification

For multi-class classification, XGBoost extends its objective function by employing the SoftMax loss, which generalises the logistic loss to accommodate multiple classes. In this setting, the model is trained to predict a probability distribution over K classes for each instance, and the final prediction corresponds to the class with the highest predicted probability.

The use of XGBoost aligns well with SHAP through the application of TreeSHAP, a variant specifically designed for tree-based models. TreeSHAP enables efficient and exact computation of SHAP values by leveraging XGBoost's hierarchical structure, providing both scalability and theoretical consistency in feature attribution (Lundberg, Erion and Lee, 2018). As summarised in **Table 2.5**, numerous prior studies have adopted this XGBoost–SHAP pairing for explainable clustering tasks, underscoring its effectiveness in producing explainable and computationally efficient models (Molnar, 2025; Lundberg and Lee, 2017). This study builds on that foundation by integrating these tools to provide transparent insights into bidder heterogeneity.

Mathematical Foundations

The SoftMax loss for a single training instance is defined as:

$$L(y_i, \hat{y}_i) = -\log\left(\frac{e^{\hat{y}_{i,y_i}}}{\sum_{k=1}^K e^{\hat{y}_{i,k}}}\right)$$

where, $y_i \in \{1, \dots, K\}$ is the true class label, $\hat{y}_{i,k}$ is the predicted raw score (logit) for class k , and $\hat{y}_{i,y_i}$ denotes the predicted score for the true class.

XGBoost internally constructs K separate trees per iteration—one for each class—and jointly optimises them to minimise the multi-class loss. This approach allows the model to learn inter-class distinctions effectively, even when class boundaries are non-linear or overlapping.

To evaluate multi-class classification performance, XGBoost supports a range of metrics including macro/micro-averaged F1-score, precision, recall, and overall accuracy. These metrics can be monitored during training to guide early stopping or hyperparameter tuning. In practice, XGBoost's capability to scale across multiple classes while maintaining robustness and accuracy makes it highly suitable for multi-class tasks in fields such as image classification, text categorisation, and fault diagnosis in complex systems.

3.4.3.5 Cross-validation

Cross-validation (CV) is a fundamental model evaluation technique in ML, designed to assess generalisability to unseen data and to prevent overfitting. Beyond performance evaluation, CV is a valuable diagnostic tool for detecting model overfitting or underfitting. Trends in cross-validated metrics can help identify overfitting or underfitting, informing decisions on model selection, hyperparameter tuning, and feature engineering.

Among various strategies, K-Fold cross-validation is widely adopted due to its favourable balance between statistical robustness and computational efficiency. In K-Fold CV, the dataset is partitioned into k equally sized subsets or folds. As illustrated in **Figure 3.4**, the model

iteratively trained on $k - 1$ folds and validated on the remaining fold. This process is repeated k times so that each fold serves exactly once as the validation set. The final performance metric is calculated as the average of all k iterations, ensuring that each data point is used for training and validation. This comprehensive process yields an unbiased and stable estimate of model performance, addressing the limitations associated with single train-test splits.

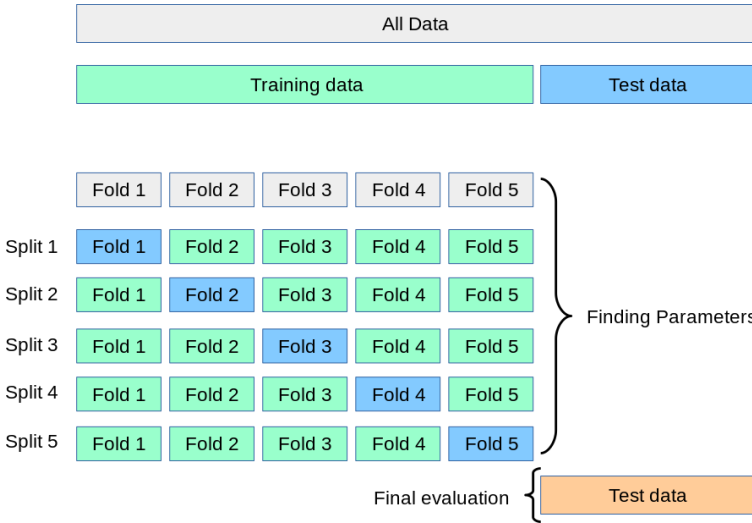


Figure 3.4: Diagram of the K-Fold Cross-Validation Method*

This study explicitly employs K-Fold CV, not holdout splitting. While holdout splitting (e.g., 80–20 split) involves training and evaluating the model on fixed subsets of data, it can produce high-variance estimates that are sensitive to the particular split used. In contrast, K-Fold CV significantly reduces this variance by averaging performance across multiple folds, thereby enhancing statistical reliability and robustness (Kohavi, 1995; Fushiki, 2011). It also maximises data utilisation, which is particularly advantageous in smaller datasets.

* Figure from Scikit learn

This study adopts 10-Fold CV as a standard evaluation strategy, given its well-established effectiveness in balancing bias and variance in model performance assessment (Kohavi, 1995; Fushiki, 2011; Rodriguez, Perez and Lozano, 2010). In recognition of the potential variability arising from a single data partitioning, particularly in datasets with limited size or high variance, repeated CV is further employed, averaging results across multiple independent runs to improve the robustness and reliability of performance estimates (Vanwinckelen and Blockeel, 2012). Specifically, and in line with the methodology of Van Nguyen *et al.* (2020), 10-Fold CV was repeated three times. This repeated procedure mitigates resampling bias and yields more stable, generalisable performance estimates.

3.4.3.6 Hyperparameter Tuning

Optimising a ML model often requires more than relying on default hyperparameter settings, which seldom yield optimal performance (Yang and Shami, 2020; Du, Xu and Zhu, 2021). Hyperparameter tuning is especially crucial for complex algorithms, such as tree-based methods (e.g., RF, XGBoost) and deep learning architectures, due to the multitude of parameters that can significantly influence model accuracy and generalisability. Properly tuned hyperparameters can significantly enhance predictive performance, accelerate convergence, and improve overall model robustness (Yang and Shami, 2020; Du, Xu and Zhu, 2021).

This study employs automated tuning techniques, specifically grid search and random search, to optimise hyperparameters across multiple models. Grid search systematically examines all possible combinations within a defined parameter grid, offering a comprehensive yet computationally intensive exploration of a limited search space (Bergstra and Bengio, 2012). In contrast, random search selects parameter combinations at random from specified

distributions, allowing for broader and often more efficient coverage of the hyperparameter space, particularly when optimal ranges are uncertain or extensive (Bergstra and Bengio, 2012). Both approaches are integrated with CV or hold-out validation to mitigate overfitting and ensure robust evaluation across different data splits. These automated strategies systematically identify hyperparameter configurations that maximise predictive accuracy while balancing computational efficiency.

3.4.4 Model Evaluation

Model evaluation is a crucial component of the data mining process, aimed at ensuring that models not only perform well on training data but also generalise effectively to unseen data. This step mitigates the risk of overfitting and underpins the generation of reliable, data-driven insights. Beyond its technical function, model evaluation reflects the principles of a positivist research paradigm, which emphasises objectivity, replicability, and empirical validation. In the context of this study's inductive analytical approach, evaluation serves as a mechanism for distinguishing genuine patterns from noise, thereby reinforcing both the statistical robustness and theoretical relevance of the findings.

3.4.4.1 Evaluation Metrics for Regression

To measure regression model efficacy, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2) are used. These metrics are effective in evaluating the performance of both statistical LR and ML models. In this study, these are used as the primary metrics to evaluate both LR and ML models.

- **Mean Absolute Error (MAE)**

Mean Absolute Error (MAE) quantifies the average absolute difference between predicted values (X_i) and actual target values (Y_i). It is calculated as:

$$MAE = \frac{1}{m} \sum_{i=1}^m |X_i - Y_i|$$

where m represents the total number of data points.

MAE provides a direct measure of prediction error in the same units as the target variable, making it highly intuitive and easy to interpret. Since it considers the absolute differences, MAE treats all deviations equally and is less sensitive to outliers compared to metrics that square the errors. This makes MAE particularly useful for obtaining a straightforward assessment of model accuracy, especially when the dataset contains extreme values.

- **Root Mean Square Error (RMSE)**

Root Mean Squared Error (RMSE) is computed by taking the square root of the average squared differences between predicted and actual values:

$$RMSE = \sqrt{\frac{1}{m} \sum_{i=1}^m (X_i - Y_i)^2}$$

RMSE offers an intuitive measure of prediction error by representing the average error in the same units as the target variable. While it penalizes larger errors more heavily, which can be beneficial in highlighting significant deviations, its sensitivity to outliers can sometimes distort the overall performance evaluation.

- **Coefficient of determination (R^2)**

The Coefficient of Determination, denoted as R^2 , measures the proportion of variance in the dependent variable that is explained by the independent variables in the model. It is defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

where $\bar{Y} = \frac{1}{m} \sum_{i=1}^m Y_i$ is the mean of the actual target values. An R^2 value of 1 indicates that the model perfectly explains the observed variance, while values closer to 0 suggest that the model does not capture much of the variability. R^2 provides insight into the model's overall goodness of fit and it is recommended for its interpretability and relevance in model performance analysis Chicco, Warrens and Jurman (2021).

However, R^2 can be overly optimistic for LR models when multiple predictors are included, as it tends to increase with the addition of variables regardless of their true explanatory power. To counteract this, Adjusted R^2 is used. Adjusted R^2 refines the R^2 measure by accounting for the number of predictors relative to the number of data points:

$$\text{Adjusted } R^2 = 1 - \left(\frac{(1 - R^2)(m - 1)}{m - p - 1} \right)$$

where m is the number of observations and p is the number of predictors.

This adjustment penalizes the inclusion of non-informative variables, offering a more balanced evaluation of model performance when comparing models with differing numbers of explanatory variables.

Despite its utility in traditional statistical analysis, Adjusted R^2 is not applied in this study for several reasons. First, Adjusted R^2 is specifically designed for statistical LR models and thus does not effectively evaluate non-linear models or complex interactions common in ML techniques. Second, Adjusted R^2 penalises model complexity based on degrees of freedom associated with additional predictors. However, in many ML methods, particularly those involving non-linear relationships or regularisation—the concept of degrees of freedom is either undefined or challenging to quantify accurately, making Adjusted R^2 unsuitable for reliable model assessment. Additionally, since this study evaluates multiple models (OLS, Ridge, Lasso, CART, RF, XGBoost) using the same train-test dataset split and employs cross-validation for performance assessment, the use of Adjusted R^2 would be methodologically inappropriate and inconsistent for comparing these diverse modelling techniques.

- **Selecting Appropriate Metrics**

As a single metric cannot provide a comprehensive evaluation of model performance, using multiple metrics is essential for a balanced and rigorous assessment (Chai and Draxler, 2014). MAE and RMSE quantify the prediction errors, while R^2 assesses the model's ability to explain variance in the data. This study adopts all three to assess the performance of LR and ML models, ensuring a thorough evaluation of both predictive accuracy and goodness of fit.

3.4.4.2 Evaluation Metric for Clustering

In unsupervised clustering, the absence of ground truth labels makes evaluation metrics essential for ensuring the reliability and interpretability of the results. Clustering evaluation methods are generally classified into two main categories: internal and external, distinguished primarily by the availability of “ground truth” predefined labels. External evaluation requires such labels for direct comparison, whereas internal evaluation does not.

Given that this study operates without pre-defined labels, internal evaluation is indispensable for assessing the clustered results based on the bidder characteristics. It assess clustering quality by relying solely on the inherent structure of the data. Performance is quantified using metrics such as intra-cluster cohesion and inter-cluster separation, which are essential for determining compactness of clusters and the degree of distinction between them. These metrics are also critical for identifying the optimal number of clusters, a central challenge in unsupervised learning. By contrast, external evaluation is applicable when ground truth labels exist. They assess clustering performance by comparing the generated clusters against known classifications, offering an objective benchmark for evaluating the algorithm’s capacity to uncover the true underlying structure. This enhances the robustness of the analysis and enables meaningful comparisons across different algorithms and parameter settings.

In this study, two robust internal metrics—the Silhouette Score and the Calinski-Harabasz Index—are employed to thoroughly assess clustering performance on unlabelled data. These metrics are widely recognised for capturing both intra-cluster cohesion and inter-cluster separation, providing a balanced and comprehensive evaluation of clustering quality. Unlike Within-Cluster Sum of Squares (WCSS), which solely measures intra-cluster cohesion, these

metrics offer a more holistic view by simultaneously accounting for how distinct and well-separated the clusters are from one another.

- **Silhouette Coefficient**

The Silhouette Coefficient (SC), introduced by Rousseeuw (1987), measures clustering quality on individual data point basis by comparing each point's cohesion (the average distance to all other points in its cluster) with its separation (the smallest average distance to points in any other cluster). The coefficient ranges from -1 to 1 , where values near 1 indicate that the data point is well-clustered, values around 0 suggest it lies on the boundary between clusters, and negative values may signal misclassification. Specifically, SC values of 0.71 – 1.00 denote strong clustering, 0.51 – 0.70 indicate reasonably structured clusters, 0.26 – 0.50 are weak, and 0.25 or below imply little to no cluster structure (Struyf, Hubery and Rousseeuw, 1997).

Mathematical Foundations

The Silhouette Coefficient measures the quality of a clustering solution on a per-data-point basis, allowing us to assess how well each individual point is assigned to its cluster relative to other clusters. It combines two primary components:

Intra-Cluster Distance, $a(i)$:

This is defined as the average distance between a data point i and all other points within the same cluster C_i . It quantifies the cohesion within the cluster. Mathematically, it is expressed as:

$$a(i) = \frac{1}{|C_i| - 1} \sum_{j \in C_i, j \neq i} d(i, j)$$

where $|C_I|$ is the number of points in cluster C_I , $d(i, j)$ represents the distance between data points i and j .

Inter-Cluster Distance, $b(i)$:

This is defined as the minimum average distance between the data point i and all points in any other cluster C_J (where $J \neq I$). It measures how well-separated the point is from the closest neighboring cluster. The calculation is given by:

$$b(i) = \min_{J \neq I} \frac{1}{|C_J|} \sum_{j \in C_J} d(i, j)$$

Silhouette Coefficient, $s(i)$

Using these two values, the Silhouette Coefficient for a data point i is computed as:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

This metric not only provides insight into the quality of individual point assignments but also allows an aggregate measure (by averaging $s(i)$ over all points) that reflects the overall clustering performance.

Advantages and Disadvantages

This metric offers advantage of providing a point-level validation of clustering quality by evaluating both intra-cluster cohesion and inter-cluster separation. Its formulation is versatile supporting various distance metrics such as Euclidean or Manhattan distances (Rousseeuw, 1987). However, the SC is sensitive to outliers, as anomalous points can skew the average distance calculations, potentially leading to misleadingly low scores. Furthermore, it is most

effective when clusters are roughly spherical, making it less reliable for irregular or non-convex cluster shapes (Rousseeuw, 1987; Monshizadeh *et al.*, 2022). The computational expense is also a consideration, given the need to calculate distances between each pair of data points.

- **Calinski-Harabasz (CH) Index**

In contrast to the local perspective provided by the SC, the Calinski-Harabasz (CH) index, also known as the Variance Ratio Criterion (Caliński and Harabasz, 1974), evaluates clustering quality on a global scale. This metric compares the variation between clusters (Between-Cluster Sum of Squares, BCSS) with the variation within clusters (Within-Cluster Sum of Squares, WCSS), thereby balancing the trade-off between cluster compactness and separation. Higher CH scores suggest that the clusters are both internally coherent and well-separated, reflecting a desirable clustering structure.

Mathematical Foundations

The CH Index is calculated as:

$$CH = \frac{BCSS/(k - 1)}{WCSS/(N - k)}$$

where N is the total number of data points, k is the number of clusters, BCSS measures the variability between clusters, WCSS quantifies the variability within clusters.

Between-Cluster Sum of Squares (BCSS):

The BCSS is computed as:

$$BCSS = \sum_i^k n_i \|c_i - c\|^2$$

with n_i being the number of data points in cluster i , c_i the centroid of cluster i , c the overall centroid of the entire dataset, $\|c_i - c\|^2$ the squared Euclidean distance between the cluster centroid and the overall centroid.

Within-Cluster Sum of Squares (WCSS):

Conversely, WCSS aggregates the squared distances between each point and its respective cluster centroid. The WCSS is calculated as:

$$WCSS = \sum_{i=1}^k \sum_{X \in C_i} \|X - c_i\|^2$$

where, C_i represents the set of data points that in cluster i , c_i is the centroid of cluster i , $\|X - c_i\|^2$ is the squared Euclidean distance between the data point X and the centroid c_i .

Advantages and Disadvantages

The CH score offers a significant advantage in computational efficiency by providing a global measure of clustering quality. It achieves this by comparing the dispersion between clusters (i.e., BCSS) to the dispersion within clusters (i.e., WCSS) (Caliński and Harabasz, 1974). This metric is particularly effective for determining the optimal number of clusters in distance-based clustering methods. However, its performance can be influenced by variations in cluster size and density. For instance, in density-based clustering scenarios, the CH score may offer a less reliable indication of the optimal clustering solution.

3.4.4.3 Evaluation Metric for Classification

To evaluate the performance of classification models, it is essential to use a set of complementary metrics that capture various aspects of predictive accuracy. This study utilises four evaluation metrics: Accuracy Score, Recall and Precision, Confusion Matrix-based Prediction, and F1 Score. These metrics offer a comprehensive and nuanced assessment of the model's ability to distinguish between classes and its capacity to generalise to unseen data.

- **Accuracy score**

The Accuracy Score is one of the most basic yet informative performance metrics. It measures the proportion of correctly classified instances out of the total number of predictions made. It is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP (True Positives) is correctly predicted positive instances, TN (True Negatives) is correctly predicted negative instances, FP (False Positives) is incorrectly predicted positive instances, FN (False Negatives) is incorrectly predicted negative instances.

While accuracy offers a broad overview of model performance, it can be misleading in the context of imbalanced datasets, where the majority class disproportionately influences the prediction outcomes. For example, a model that consistently predicts only the majority class may exhibit high accuracy, despite failing to identify instances of the minority class. Therefore, accuracy must be interpreted alongside other metrics, especially when class distribution is skewed, to obtain a more reliable assessment of model effectiveness.

- **Recall and Precision**

Recall and Precision are critical evaluation metrics, particularly in scenarios where the cost of false positives or false negatives is high. Recall and Precision are critical evaluation metrics, particularly in scenarios where the cost of false positives or false negatives is substantial. Their importance is underscored in high-stakes applications, where even minor classification errors can undermine system reliability, affect user trust, or lead to operational and financial risks.

Recall (also known as Sensitivity or True Positive Rate) measures the model's ability to correctly identify all actual positive cases. It is defined as:

$$Recall = \frac{TP}{TP + FN}$$

High recall is essential when failing to detect positive cases is costly, for example, overlooking fraudulent transactions or undiagnosed medical conditions.

Precision quantifies the proportion of predicted positive instances that are actually correct. It is calculated as:

$$Precision = \frac{TP}{TP + FP}$$

High precision is vital when false positive are expensive, such as mistakenly flagging legitimate transactions as fraudulent or issuing unnecessary medical alerts.

There is often a trade-off between precision and recall. Therefore, they must be evaluated together, with the balance depending on the specific objectives and risk tolerances of the application domain.

- **Prediction and Confusion Matrix**

Prediction refers to the model's assignment of class labels to individual instances. To evaluate the effectiveness of these predictions, a confusion matrix is employed. This matrix provides a structured summary by comparing the predicted class labels against the actual labels, offering insight into the model's performance across true positives, true negatives, false positives, and false negatives.

Table 3.1: Prediction and Confusion Matrix

	Predictive Positive	Predictive Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

The confusion matrix provides a detailed breakdown of prediction outcomes, allowing for more granular performance analysis. It is particularly helpful in identifying specific types of errors (e.g., false positives vs. false negatives), guiding decisions on whether to prioritise sensitivity or specificity in model tuning.

- **F1 Score**

The F1 Score is the harmonic mean of Precision and Recall, offering a single, balanced metric that is especially effective in contexts with imbalanced class distributions. It is defined as:

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

The F1 Score is particularly valuable when both Precision and Recall are critical to the problem domain, and one cannot be improved without compromising the other. A high F1 Score indicates that the model is accurately identifying the positive class while minimising both false positives and false negatives.

3.4.5 Model Deployment

While model evaluation marks a critical point in the data mining process, the final and most impactful stage is model deployment, where analytical insights are translated into actionable strategies. In this study, deployment involves interpreting predictive model outputs to inform managerial decision-making in the remanufactured electronics sector.

To facilitate this, the study employs a combination of model-agnostic interpretability techniques that offer both global and local insights. At the global level, Feature Importance (FI) and Partial Dependence Plots (PDPs) are used to identify key predictors influencing on predicted auction prices and bidder clustering. FI ranks variables based on their contribution to model output, while PDPs illustrate how changes in a specific feature affect predictions on average across the dataset. For local-level interpretability, SHAP is integrated to explain individual predictions. SHAP values quantify how each feature contributes to a specific prediction, offering granular transparency into the model's decision logic based on game theory.

This dual-layered approach combining FI and PDP with SHAP ensures both a high-level understanding of auction price drivers and detailed explanations at the individual level. Such interpretability strengthens trust, transparency, and accountability, transforming complex models into practical tools for strategic and operational improvement.

3.4.5.1 SHapley Additive exPlanation (SHAP)

SHAP is a model-agnostic post-hoc interpretability method within the field of XAI that provides both local and global insights into ML model predictions. As a post-hoc approach, SHAP does not interfere with the model training process but instead interprets the model after it has been trained, making it broadly applicable across a wide range of model types, including regression, classification, and ensemble methods. Compared to alternative methods such as LIME or permutation importance, SHAP offers greater stability, consistency, and the ability to capture both global and local effects. Unlike LIME, which can be sensitive to perturbations, SHAP provides theoretically grounded attributions that are more reliable (Molnar, 2025).

Rooted in cooperative game theory, SHAP builds upon the Shapley value framework developed by Shapley (1953), which ensures a fair allocation of contributions among players—in this context, input features—based on their marginal impact on the model’s output. SHAP quantifies the contribution of each feature to a specific prediction, ensuring that the sum of all feature attributions equals the model’s output. It satisfies key theoretical properties such as local accuracy, consistency and additivity, offering a mathematically sound and transparent mechanism for interpreting complex models. The Shapley-based interpretability method was formalised by Lundberg and Lee (2017) and later expanded into the SHAP framework by Lundberg, Erion and Lee (2018) and Lundberg *et al.* (2019).

Mathematical Foundations

SHAP relies on the principles of cooperative game theory to fairly attribute the contribution of each input feature to a ML model’s output. In this framework, each feature is conceptualised as a player in a cooperative game, and the model’s prediction is the payout to be fairly distributed

among all features. The contribution of a feature is calculated using the Shapley value, a method introduced by Shapley (1953), which considers the average marginal contribution of a feature across all possible subsets of features.

Formally, the Shapley value for feature i is defined as:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|! (|N| - |S| - 1)!}{|N|!} (f(S \cup \{i\}) - f(S))$$

where ϕ_i is the Shapley value for feature i , S is any subset of features excluding i , N is the set of all features, $f(S)$ denotes the model's prediction based only on the features in subset S , $f(S \cup \{i\})$ is the prediction when feature i is added to the subset S .

This formulation ensures fairness by evaluating the contribution of each feature across all possible combinations, thereby satisfying key theoretical properties such as efficiency, symmetry, dummy and additivity (Molnar, 2025).

For linear models, SHAP values simplify to a more interpretable form. Given a model:

$$\hat{f}(x) = \beta_0 + \sum_{j=1}^p \beta_j x_j$$

The SHAP value for feature j becomes:

$$\phi_j(\hat{f}) = \beta_j x_j - E(\beta_j X_j) = \beta_j (x_j - E(X_j))$$

Summing across all p features results in:

$$\begin{aligned}
\sum_{j=1}^p \phi_j(\hat{f}) &= \sum_{j=1}^p (\beta_j x_j - E(\beta_j X_j)) \\
&= \left(\beta_0 + \sum_{j=1}^p \beta_j x_j \right) - \left(\beta_0 + \sum_{j=1}^p E(\beta_j x_j) \right) = \hat{f}(x) - E(\hat{f}(X))
\end{aligned}$$

For non-linear or complex models, the Shapley value remains:

$$\phi_j(f, x) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|! (|N| - |S| - 1)!}{|N|!} \left[(f_{S \cup \{j\}}(x) - f_S(x)) \right]$$

In practical applications, calculating exact Shapley values becomes computationally expensive due to the factorial term. Therefore, approximation methods are employed, where the value is estimated over M samples:

$$\phi_j(x) \approx \frac{1}{M} \sum_{m=1}^M \phi_j^{(m)}$$

The complete SHAP explanation model is then:

$$g(x') = \phi_0 + \sum_{j=1}^M \phi_j$$

This decomposition provides both global interpretability (feature importance across the dataset) and local interpretability (feature impact for individual predictions), making SHAP a robust tool for interpreting ML models. Its theoretical grounding ensures that explanations are not only consistent and fair but also meaningful in real-world decision-making contexts.

TreeSHAP

A core limitation of traditional Shapley value computation lies in its factorial complexity, which becomes computationally prohibitive in high-dimensional settings. To address this, Lundberg, Erion, and Lee (2018) introduced TreeSHAP, a specialised and efficient variant of SHAP tailored for decision tree-based models. By leveraging the recursive, hierarchical structure of tree ensembles, TreeSHAP enables the exact computation of SHAP values without the need to exhaustively enumerate all possible feature coalitions, thereby significantly reducing computational overhead. Unlike standard SHAP, which estimates feature contributions based on marginal expectations over all possible feature subsets, TreeSHAP reformulates the attribution mechanism using conditional expectations, defined as:

$$E(f(x)|x_j)$$

This adjustment allows TreeSHAP to preserve SHAP's desirable theoretical properties, namely local accuracy, consistency, and additivity, while ensuring computational scalability in large-scale, tree-based learning environments.

Crucially, TreeSHAP is natively compatible with gradient boosting frameworks such as XGBoost, making it particularly well-suited to the current study's analytical architecture. As this research employs XGBoost to model auction price dynamics and to identify influential market signals, TreeSHAP facilitates a transparent, feature-level interpretation of the model's output. This is essential not only for identifying the global drivers of pricing outcomes but also for generating locally faithful explanations of individual predictions, aligning directly with the study's emphasis on interpretability and actionable insight.

Advantages and Disadvantage of SHAP (TreeSHAP)

SHAP (TreeSHAP) offers several critical strengths and some notable limitations when applied to model interpretation, particularly in tree-based ML frameworks such as XGBoost and RF:

- **Model-Agnostic Flexibility:** SHAP can be applied across a wide range of ML models—both linear and non-linear—without requiring changes to the model structure, offering broad applicability in both regression and classification tasks (Lundberg and Lee, 2017).
- **Global and Local Interpretability:** SHAP provides consistent explanations at both the global and individual levels. Globally, it identifies overall feature importance across the dataset, while locally, it explains how each feature contributed to a specific prediction (Chen *et al.*, 2023).
- **Theoretical Soundness:** Rooted in cooperative game theory, SHAP satisfies critical properties such as local accuracy, consistency and missingness, which ensure fair and reliable attributions of feature contributions (Shapley, 1953).
- **Computational Efficiency in Tree-Based Models:** TreeSHAP, an optimised variant, leverages the internal structure of decision trees to compute exact Shapley values with significantly reduced computational cost, enabling practical application to large-scale datasets and high-dimensional feature spaces (Lundberg, Erion and Lee, 2018).
- **Reproducibility and Stability:** Unlike LIME, SHAP produces stable and consistent attributions, making it preferable in applications where interpretive reliability and model accountability are critical (Ribeiro, Singh and Guestrin, 2016; Molnar, 2025).

On the other hand, SHAP also has disadvantages:

- **Limited Scope of TreeSHAP:** Although TreeSHAP is efficient, it is specifically tailored to decision tree-based models and cannot be applied to non-tree architectures, reducing its generalisability across model types (Lundberg, Erion and Lee, 2018).

- **Unintuitive Attributions:** In some cases, TreeSHAP may assign non-zero importance to features that appear unrelated to the prediction. This stems from its reliance on conditional expectations, which can mask true causal relationships and potentially mislead interpretation (Chen *et al.*, 2023).
- **Computational Complexity in General SHAP:** Outside of TreeSHAP, standard SHAP implementations (e.g., KernelSHAP) suffer from high computational overhead, particularly when dealing with large datasets or models with numerous features. This limits scalability in real-time or resource-constrained environments (Molnar, 2025).
- **Interpretation Risks:** Shapley values quantify a feature's contribution relative to a baseline prediction, not the effect of removing the feature altogether. Misunderstanding this nuance can result in incorrect inferences about causality or feature relevance, especially among non-expert users (Molnar, 2025).

In summary, TreeSHAP offers a robust, theoretically grounded, and computationally efficient method for interpreting complex models based on tree ensembles. While its applicability is limited to tree-based algorithms, it remains one of the most dependable tools for producing transparent and fine-grained explanations. This is especially valuable in contexts such as remanufactured product auctions, where interpreting subtle feature interactions is critical for understanding bidder behaviour and pricing dynamics.

SHAP-Based Interpretability Framework for This Study

SHAP is adopted in this study to improve the interpretability of both regression and clustering models, offering a unified, model-agnostic framework rooted in cooperative game theory. This approach is particularly well-suited to the study's three core objectives: (1) understanding the

influence of market signals on auction prices for remanufactured electronics (RQ1), (2) assessing how these effects vary by product condition (RQ2), and (3) examining bidder heterogeneity through clustering (RQ3).

Across these contexts, model explainability is essential due to the black-box nature of ML models. While ML offers strong predictive performance, it often lacks interpretability, especially problematic in markets with high information asymmetry. To address this, SHAP is incorporated to enhance transparency, providing post-hoc explanations of feature contributions. This approach overcomes the limitations seen in studies like Van Nguyen *et al.* (2020), which lacked tools to analyse complex, non-linear interactions in auction data.

In the two regression contexts for first and second research, SHAP explains how each input feature contributes to the predicted auction price for a given listing. This supports the study's objective of identifying which market signals, such as feedback score, product condition or product description sentiment, drive price formation. Unlike traditional feature importance metrics, SHAP provides individual-level explanations, offering granular insights into model behaviour across varying auction conditions. This aligns with the study's emphasis on performance and explainability in predictive modelling.

In the clustering context, SHAP is employed post-hoc by re-framing cluster assignments as a supervised classification problem, allowing for the quantification of each feature's influence on cluster membership. This is critical to the study's third objective—understanding bidder heterogeneity—by identifying the distinguishing characteristics of each bidder segment. SHAP facilitates identification of contribution of each feature, bridging the gap between unsupervised

learning and explainability. It allows for a structured analysis of the behavioural traits that define different bidder types, transforming black-box clustering results into explainable profiles.

By integrating SHAP into both predictive and exploratory stages of the analysis, the study ensures a transparent, interpretable, and theoretically grounded modelling approach. This not only enhances trust in the model outputs but also supports data-driven decision-making in the context of remanufactured product auctions.

3.4.5.2 Feature Importance

Feature importance is a critical method in ML for providing global, model-agnostic explanations. It evaluates and ranks each feature based on its contribution to predicting the target variable, offering insights into the model's predictive performance. Understanding feature importance is vital for identifying the relative influence of each feature, which is crucial during model deployment. This method is intuitive and provides a straightforward way to assess the significance of variables within a model.

There are two primary methods to calculate feature importance in global, model-agnostic frameworks. Both methods provide valuable insights into how individual features influence the model's predictions, helping practitioners better understand model behaviour and make informed decisions during deployment. Feature importance can also be further enhanced with advanced techniques such as SHAP.

- **Mean Decrease in Impurity (MDI)** is frequently used with decision tree-based algorithms. It calculates feature importance by measuring the reduction in impurity (such as Gini impurity or entropy) when data is split based on a particular feature. The greater the

reduction in impurity, the more important the feature is considered.

- **Permutation Feature Importance (PFI)** measures the change in the model's performance when a feature's values are randomly shuffled. If performance drops significantly after shuffling, the feature is deemed important.

Integration with SHAP

Feature importance can be significantly enhanced through the use of SHAP, a method rooted in cooperative game theory. SHAP offers a principled and statistically rigorous approach to quantifying the contribution of individual features to model predictions. Unlike traditional methods, which merely rank features by their absolute importance, SHAP goes further by allowing practitioners to assess both the direction (positive or negative) and magnitude of each feature's impact on predictions.

The SHAP feature importance for a given feature j is computed as the mean absolute Shapley value across all observations:

$$\text{Feature Importance (SHAP)} = \frac{1}{N} \sum_{i=1}^N |\phi_j^{(i)}|$$

where $\phi_j^{(i)}$ denotes the SHAP value of feature j for the i -th instance, and N is the total number of instances. This formulation captures the average contribution of each feature across the dataset, providing a more comprehensive measure of importance than simple ranking methods.

SHAP values are typically visualised using summary plots, such as the beeswarm plot, which simultaneously conveys the magnitude, direction, and distribution of feature contributions.

Unlike conventional bar charts that display only average importance, beeswarm plots illustrate how individual feature values influence predictions, making it easier to identify both consistent patterns and outliers in model behaviour. This enhances transparency and supports more informed model interpretation.

Compared to traditional techniques like Permutation Feature Importance (PFI), which assesses importance based on changes in model performance after random shuffling (Molnar, 2025), SHAP offers a model-agnostic, locally consistent alternative that does not require retraining or perturbation. While PFI focuses on global performance degradation, SHAP highlights the nuanced, instance-level contributions of each feature, enabling global and local explanation.

Nevertheless, while SHAP feature importance plots provide strong global interpretability, they do not inherently capture interaction effects or conditional dependencies between features. To address this, complementary tools such as Partial Dependence Plots (PDPs) or SHAP dependence plots can be employed. These visualisations extend the explanatory power of SHAP by revealing how feature values influence predictions across different contexts, supporting a deeper understanding of complex model dynamics.

3.4.5.3 Partial Dependence Plot (PDP)

The Partial Dependence Plot (PDP) is a widely used global, model-agnostic method for visualizing the marginal effect of one or two features on the predictions of a ML model (Friedman, 2001). PDPs allow practitioners to observe how specific features influence model outputs, offering crucial insights into the relationships between input variables and target outcomes. This technique is particularly valuable for identifying whether a feature's

relationship with the target is linear, monotonic, or more complex, revealing patterns that may not be obvious from the raw data alone. As such, PDPs are essential for understanding model behaviour and determining the key drivers behind predictions.

Mathematical Foundations

Mathematically, the partial dependence function for regression is defined as:

$$\hat{f}_S(x_S) = E_{X_C}[\hat{f}(x_S, X_C)] = \int \hat{f}(x_S, X_C) d\mathbb{P}(X_C)$$

where x_S represents the features of interest (typically one or two), and X_C includes all other features in the model, treated as random variables. The combined vectors x_S and X_C form the total feature space x . PDP works by marginalizing the model's output over the distribution of the features in X_C , isolating the effect of x_S on the predicted outcome by averaging out the influence of X_C .

To estimate the partial dependence function, the Monte Carlo method is typically employed, which averages the model predictions over the training data:

$$\hat{f}_S(x_S) = \frac{1}{n} \sum_{i=1}^n \hat{f}(x_S, x_C^{(i)})$$

where $x_C^{(i)}$ refers to the actual feature values from the dataset for features not in S , and n is the number of instances in the dataset. This approach estimates the average marginal effect of the features in S on the model's predictions.

However, a key assumption of PDP is that the features in X_C are not strongly correlated with those in x_S . When this assumption is violated, the computed averages may include unrealistic

or improbable data points, which could lead to misleading interpretations. Despite this limitation, the strength of PDP lies in its ability to clearly visualize the average effect of one or two features while accounting for the variability of other features. It remains an effective tool for explaining model behaviour in a straightforward manner.

Integration with SHAP

In this study, Partial Dependence Plots (PDPs) are augmented through integration with SHAP values to overcome the inherent limitations of traditional PDPs. While PDPs provide a global, model-agnostic view of average feature effects, they often fail to account for complex interactions and the distributional characteristics of features. By incorporating SHAP values, the SHAP dependence plots preserve interpretability while offering a more nuanced understanding of both feature effects and interactions.

Traditional PDPs illustrate the marginal effect of a feature by averaging predictions, but they can mislead when features are correlated or interact strongly. SHAP dependence plots address these shortcomings by leveraging the theoretical robustness of SHAP, which is grounded in cooperative game theory and satisfies properties such as local accuracy and consistency. This integration enables a more faithful representation of feature behaviour, particularly in models with non-linear or high-order interactions. SHAP dependence plots serve as a more informative alternative to conventional PDPs and Accumulated Local Effects (ALE) plots. Unlike PDPs and ALE, which depict only average effects, SHAP dependence plots display both the average SHAP value and its variance across observations. This variance acts as a diagnostic for interaction strength—larger dispersion implies greater interaction with other features.

Mathematical Foundations

Formally, SHAP dependence plots are constructed using the set of points:

$$\left\{ \left(x_j^{(i)}, \phi_j^{(i)} \right) \right\}_{i=1}^n$$

where $x_j^{(i)}$ represents the value of feature j for instance, and $\phi_j^{(i)}$ is the corresponding SHAP values indicating the contribution of that feature to the model's prediction. This formulation provides a complete view of how feature j influences model output across all data points.

Interpretive Value

The integration of PDP with SHAP creates a hybrid interpretability tool that combines the simplicity of global average effect visualisation with the precision and depth of SHAP-based local explanations. This approach is especially useful for detecting non-linearities and interactions in complex models. It supports more transparent and trustworthy model interpretation, essential for decision-making in high-stakes environments such as remanufactured product auctions, where both performance and interpretability are critical.

3.5 Summary

This chapter established the methodological framework underpinning the study, anchored in a positivist research philosophy that prioritises objective measurement, empirical observation, and replicable analysis. The selected research design—quantitative, exploratory, inductive, and cross-sectional—was purposefully structured to investigate the underexplored domain of remanufactured product auctions, with particular focus on consumer behaviour, pricing dynamics, and bidder heterogeneity.

The study employed secondary data collected from eBay auctions, enabling large-scale empirical investigation without the constraints of experimental control. This approach supports the inductive development of theory from observed patterns in real-world transactions. Analytical techniques included regression to model price determinants, clustering to identify latent bidder segments, and classification to further explain group-level differences. These three methods were chosen for their complementary strengths in capturing both linear and non-linear relationships, offering a holistic view of auction outcomes.

In line with the study's emphasis on transparency and interpretability, the chapter also introduced model validation procedures and explainability strategies. Validation ensured robustness by confirming that discovered patterns were generalisable and not artefacts of noise or overfitting. Meanwhile, the integration of SHAP enhanced the explainability of complex ML models by providing feature-level insights into both global and individual predictions.

Throughout the chapter, methodological decisions were guided not only by theoretical coherence but also by practical considerations, ensuring that the chosen techniques yield actionable findings for academics, platform designers, and sellers. This well-defined methodological framework provides the empirical and conceptual foundation for the analysis in subsequent chapters, supporting both the rigour and relevance of the research outcomes.

Chapter 4

How Market Signals Shape Online Auction Prices for Remanufactured Electronics: An Explainable AI Approach

4.1 Introduction

This chapter investigates the impact of market signals on prices in online auctions of remanufactured goods, where information asymmetry is particularly pronounced. In such markets, buyers frequently operate under time constraints and with incomplete information regarding product quality or condition, both of which significantly influence auction outcomes and undermine overall market efficiency. Within this context, the three primary stakeholders—sellers, bidders, and platforms—emit various signals aimed at mitigating adverse selection and preserving market integrity by influencing price formation.

The objective of this study is to extend existing understanding of remanufactured goods beyond fixed-price markets by analysing how these signals affect auction prices. In particular, this study compares ML with conventional statistical methods, demonstrating the superiority of the former. To address the inherent black-box limitations of ML, it applies XAI techniques,

specifically SHAP, to identify the key factors driving price increases and to provide insights into how these elements interact to shape auction dynamics.

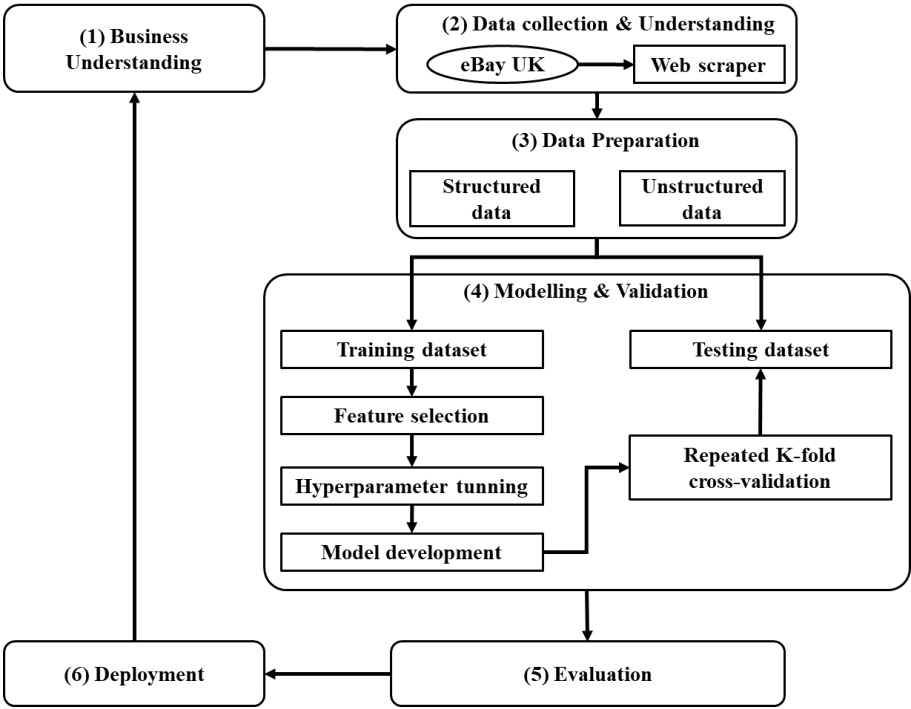


Figure 4.1: Overview of the Methodological Framework

Figure 4.1 illustrates the CRISP-DM framework, which forms the structural foundation of this chapter and comprises six phases, each tailored to the specific objectives of this study. The chapter is organised in alignment with these core analytical stages, providing a systematic and rigorous approach to the data mining process. Section 4.2, corresponding to the Data Understanding phase, introduces the dataset, describes its key characteristics, and evaluates data quality through exploratory data analysis. Section 4.3 addresses Data Preparation, encompassing data construction, cleaning, feature selection, and formatting to establish a solid analytical foundation. Section 4.4 covers Modelling and Validation, detailing model development and validation techniques adopted to ensure robustness. Section 4.5 addresses the

Evaluation phase, where model performance is quantitatively assessed. Finally, Section 4.6 covers the Deployment stage, focusing on model interpretability through SHAP values.

4.2 Data Understanding

This step entails validating the structure and content of the data using statistical metrics and visualisation techniques to ensure alignment with the chosen data mining model. A comprehensive assessment at this stage enables accurate evaluation of data quality, completeness, and suitability for analysis. Neglecting this process can result in major setbacks, including the need for data recollection or reliance on data unfit for the study.

4.2.1 Data Description

Ensuring that the dataset's format, volume, and record count align with the study's research objectives is crucial at this stage. This verification step is essential for effective data preprocessing and variable selection, which are necessary for extracting meaningful insights. By ensuring data quality early in the process, the validity of subsequent analyses is supported, thereby improving the reliability of the study's conclusions. The following sections, Data Period and Quantity and Data Format, will explore these aspects in greater detail, emphasizing their importance for the overall robustness and effectiveness of the research.

- **Data Period and Quantity**

Data collection took place from February 15th, 2023, to June 29th, 2023, during which detailed information was gathered on 1039 remanufactured electronics. These items span multiple categories, including smartphones, tablets, laptops, and small home appliances, representing a diverse range of remanufactured products available on the eBay platform. The dataset captures

both product-specific details, such as item condition, starting bid, final sale price and auction duration, as well as extensive information from the corresponding seller profiles on eBay, including seller ratings, feedback scores, and account history. This comprehensive scope of the data allows for an in-depth exploration of how different product categories and seller characteristics influence bidding strategies and final outcomes. By integrating seller metrics with product listings, the study provides a richer context for understanding price determinants and market perceptions of remanufactured electronics in online auction environments.

- **Data Format**

Various types of data were collected throughout the data collection stages, broadly categorized into structured and unstructured data. Structured data, typically quantitative in nature, comprises the majority of the dataset, consisting primarily of numerical values such as prices, feedback scores and auction durations. However, the dataset also includes unstructured data, such as product descriptions, which is qualitative and requires further processing before analysis. During the data preparation phase, both structured and unstructured data are transformed to be suitable for input into the analysis models. For instance, the product description text is processed through sentiment analysis, which generates emotion scores that can be used as input variables in the model. Additionally, categorical data, such as product types or seller attributes, is encoded into numerical form to ensure consistency and accuracy in the subsequent analysis. This transformation ensures that all data, regardless of its original format, contributes meaningfully to the study's insights on auction dynamics and bidder behaviour.

4.2.2 Dependent and Explanatory Variables

This section outlines and defines the key variables used in the analysis, including both dependent and independent variables. The selection of variables is justified with reference to relevant literature and theoretical frameworks, where appropriate. This provides transparency in the analytical approach and reinforces the validity of the study's findings.

4.2.2.1 Dependent Variable

This study adopts the final auction price as the dependent variable. Defined as the highest bid submitted at the close of an auction, this measure captures both the competitive intensity of the bidding process and the perceived value of the remanufactured product. While prior research on pricing determinants has predominantly focused on fixed-price settings within the context of consumer behaviour, a limited number of studies have incorporated auction prices as the outcome variable.

For instance, Pang *et al.* (2015) examined factors influencing the price differential between new and remanufactured products by analysing transaction data from both fixed-price and auction listings in the remanufactured electronics category on eBay UK. Xu, Zeng and He (2017) investigated consumers' WTP in auction versus fixed-price formats, identifying e-service elements that influence WTP across the two models. Casalin and Dia (2019) specifically focused on auction markets, exploring how feedback scores and alternative reputation mechanisms affect final auction prices.

4.2.2.2 Explanatory variables

This study considers that each participant—seller, buyer, and platform—in the online auction of remanufactured products convey distinct signals for successful transaction due to its uncertainty and information asymmetry. To facilitate analysis, this study has categorized the explanatory variables into three principal groups: (1) Seller-side, (2) Buyer-side, and (3) Platform-side. This framework is inspired by prior research approaches. Zhou and Gupta (2019), for example, analysed variables to determine the rates of technological and quality depreciation in smartphones, considering factors associated with sellers, services, transactions, and products. Similarly, Van Nguyen *et al.* (2020) differentiated the variables into seller-generated and user-generated content. Through this systematic analysis, this study aims to gain comprehensive insights into the multifaceted factors that contribute to mitigating information asymmetry. Detailed explanations of each participant offer insights into the dynamics of online auctions for remanufactured products.

- **Seller-side variables**

Existing research on ‘lemon markets’ and information asymmetry highlights the critical role of seller-provided information in online marketplaces, where the knowledge gap between buyers and sellers can be substantial. This challenge is especially relevant in the sale of used, remanufactured, or refurbished products, where quality and authenticity may vary significantly. In these contexts, the accuracy and reliability of seller information are key to maintaining market efficiency and fostering consumer trust. Seller-side variables, such as product descriptions, images and quality indicators, serve as essential components of this information. These details not only help prospective buyers assess the value and condition of a product but also act as signals of seller credibility and trustworthiness. In markets with high levels of

uncertainty, such as online platforms for remanufactured goods, transparency in seller communications is paramount. Clear and accurate information mitigates the risks of information asymmetry, builds buyer confidence, and supports smoother transactions. As a result, sellers who effectively communicate product details can significantly reduce market frictions and enhance their success in online auctions.

1) Starting Price (*STT_P*)

This study considers the starting price as a crucial factor in determining the final auction price. The choice of starting price is a significant strategic decision for sellers, as it can substantially influence the auction's outcome. By carefully selecting the starting price, sellers can better align their auction strategies with their objectives, whether that involves attracting a larger pool of bidders or leveraging perceptions of quality to achieve higher final prices.

There are two main perspectives in the literature regarding the impact of starting price on auction outcomes. The first suggests that lower starting prices drive up the final auction price. Several studies have found that lower starting prices reduce perceived risk for buyers (Wood *et al.*, 2005), lower entry barriers for potential bidders and increase the sunk costs (Ku, Galinsky, Murnighan, 2006; Galinsky, Ku and Mussweiler, 2009) and increase the overall number of participants (Gilkeson and Reynolds, 2003; Yu, Wang and Dang, 2006; Elhadary, 2012). This suggests that setting a low starting price attracts more bidders by lowering the entry barrier and increasing their psychological commitment through sunk costs, thereby intensifying competition and ultimately raising the final auction price to the seller's advantage.

On the other hand, some studies argue that higher starting prices can signal high product quality (Stern and Stafford, 2006; Liang and Chen, 2012; Elmaghraby, Gopal and Pilehvar, 2018) and can lead to higher final prices (Ariely and Simonson, 2003; Stern and Stafford, 2006; Liang and Chen, 2012; Liang, 2014). Stern and Stafford (2006) note that consumers often interpret a higher starting price as an indicator of quality, especially in online auctions where physical inspection is not possible, and information asymmetry exists. Simonsohn and Ariely (2008) further reveal that higher starting prices tend to result in higher winning bids, particularly when comparable items are not readily available. This perception of higher quality can justify higher bids, leading to a higher final price.

However, research by Elmaghraby, Gopal and Pilehvar (2018) offers a more complex perspective, particularly in the context of online B2B auctions. Their findings suggest that lower starting prices do not always result in higher final prices. They highlight that the effectiveness of starting price strategies can vary significantly across different market environments, challenging the conventional wisdom that lower starting prices are universally advantageous.

Drawing from the existing literature, this study incorporates the starting price as a key variable to examine its influence on final auction outcomes. Starting prices were extracted from the bidding history pages, with the majority falling below £0.99, resulting in a highly skewed distribution. To address this skewness and improve the rigor of the analysis, a logarithmic transformation is applied in the data preparation phase to the starting price data. This transformation corrected the distribution, reducing the impact of outliers and facilitating a more robust and statistically sound analysis.

2) Auction Duration (*DURAT*)

Auction duration plays a pivotal role in shaping buyer behaviour and auction outcomes on platforms like eBay, influencing both competitive dynamics and final prices. Research consistently shows that longer auction durations provide bidders with more time to engage, encouraging competitive bidding and often resulting in higher final prices.

Prior research demonstrates that longer auction durations attract more bidders, driving up prices. For example, Dewally and Ederington (2006) found that comic book auctions lasting over 10 days significantly increased bidder participation compared to 3-day auctions, leading to higher final bids. They found that 5-day auctions achieved prices 9–12% higher than shorter auctions, with diminishing returns for durations beyond 5 days. Lucking-Reiley *et al.* (2007) reinforced these findings in U.S. Indian Head penny auctions, where 7-day and 10-day auctions increased prices by 24% and 42%, respectively. However, the study also notes that longer auctions can incur higher transaction costs, potentially reducing efficiency for buyers and sellers.

Some studies offer mixed results. Haruvy and Popkowski Leszczyc (2010) found that while longer auctions on eBay led to an 11% price increase, shorter auctions on local platforms without a Buy It Now option saw a 20% price increase. This was attributed to impatient bidders engaging in more competitive bidding due to shorter timeframes. Jie and Yaping (2011) highlighted potential downsides for longer auctions, especially for rapidly depreciating products like electronics, where extended durations may lower seller revenue due to increased competition and product devaluation.

Ren and Chen (2020) further examined how auction duration affects seller revenue, showing that while longer auctions initially attract more bidders, beyond a certain point, factors such as storage costs and perishability begin to reduce potential profits. Muthitacharoen and Tams (2017) similarly found that longer auctions increase bidder costs, reducing their surplus and participation. They also note that shorter durations can exacerbate information asymmetry, as buyers have less time to assess product quality, leading to higher uncertainty and perceived risk.

Building on these insights, this study investigates auction duration as a critical seller signal in high-information-asymmetry environments, such as online auctions for remanufactured products. By analysing how auction duration influences final prices, the study aims to provide a strategic understanding of how sellers can balance the benefits of extended exposure against the risks of increased competition and declining bidder surplus.

3) Seller Feedback Scores

The feedback rating system used by eBay plays a pivotal role in mitigating information asymmetry by providing potential buyers with critical insights into seller reputation and previous customer experiences. Numerous studies emphasize the importance of customer feedback scores as key determinants of seller credibility. Feedback scores serve as an important signal to buyers, helping to reduce the uncertainty often associated with online purchases, particularly for remanufactured or refurbished products.

Research has shown that negative feedback tends to have a more substantial impact on buyer perceptions than positive feedback, as damage to a seller's reputation significantly increases perceived risk (Chevalier and Mayzlin, 2006; Cui, Lui and Guo, 2012; De Maeyer, 2012).

Moreover, Resnick and Zeckhauser (2002) and Cabral and Hortaçsu (2010) suggest that even neutral feedback can be interpreted as negative, further highlighting the sensitivity of buyer trust. Subramanian and Subramanyam (2012) found that for remanufactured products, a positive seller reputation narrows the price differential between new and remanufactured goods.

Similarly, Pang *et al.* (2015) identified seller reputation as a significant factor affecting the price gap in these markets. Mickey (2010) also demonstrated that a seller's negative rating ratio has a strong influence on the final auction price, reinforcing the idea that reputation is crucial in shaping buyer behaviour. Meanwhile, Casalin and Dia (2019) examine how feedback and reputation systems reduce information asymmetry in second-hand electronics auctions, finding feedback scores less valuable when safeguards, such as manufacturer-approved refurbishments or return policies, are in place but particularly influential for lower-priced items.

To capture this dynamic, eBay's 'feedback profile' page provides feedback scores that span different periods, including overall feedback (*FEED_S*) and recent feedback scores for the past 1, 6, and 12 months, encompassing positive, neutral, and negative reviews. eBay's system calculates the total feedback score by adding one point for each positive review, assigning zero points for neutral feedback, and deducting one point for each negative review. This calculation applies to total scores for specific timeframes (1, 6, and 12 months) as well as the overall score.

Unlike previous studies that primarily focus on total feedback or positive feedback rates, this study adopts a more comprehensive approach by incorporating feedback scores from the past 1, 6, and 12 months, along with the total score. This method allows for a deeper analysis of whether the seller is currently active and how their recent performance affects customer demand

for remanufactured products. By examining positive and negative feedback within specific timeframes, it is identified as momentum sellers, whose recent activity influences auction outcomes, providing a nuanced understanding of the relationship between seller performance and buyer behaviour.

4) Product Condition (*CONDIT*)

In online auctions for remanufactured goods, where information asymmetry is high, the Condition (*CONDIT*) variable acts as a crucial signal that sellers use to convey the quality and reliability of their products. Buyers, lacking the ability to physically inspect items, rely heavily on these condition signals to make informed decisions, reducing perceived risks associated with remanufactured products. The *CONDIT* also plays a critical role in shaping consumer WTP and purchase behaviour for remanufactured products, as well as in evaluating value differences between new and remanufactured goods (e.g., Subramanian and Subramanyam, 2012; Pang *et al.*, 2015; McKie *et al.*, 2018; Zhou and Gupta, 2020).

While previous studies have explored how product conditions, whether new, used, or remanufactured, impact pricing and sales rankings using data from platforms like eBay and Amazon (e.g., Frota Neto, Bloemhof and Corbett, 2016; Xu, Zeng and He, 2017; McKie *et al.*, 2018), this study extends the analysis by examining product conditions with greater granularity. By providing a more detailed view of specific condition levels, the study sheds light on how these signals influence buyer behaviour and auction outcomes, addressing gaps in the literature and offering insights into how sellers can more effectively communicate product quality in markets with significant information asymmetry.

To investigate the effect of product condition on auction outcomes, this study collects detailed condition information for remanufactured electronics from eBay, ranging from Good to Certified-Refurbished. The highest rating, Certified-Refurbished, indicates a manufacturer-approved refurbishment process, while other ratings such as Excellent, Very Good and Good reflect varying degrees of refurbishment, which may not necessarily be manufacturer-approved under eBay's Refurbished Programme.

By focusing on these finer distinctions in product condition, this study aims to uncover how specific refurbishing grades influence value and consumer trust, offering a deeper understanding of consumer behaviour and market dynamics in the remanufactured goods sector. This detailed approach enriches current insights into how consumers perceive and respond to product conditions, particularly in online marketplaces.

5) Number of Pictures (*NUMPIC*)

In the digital marketplace for remanufactured goods, where physical inspection is impossible and information asymmetry is prevalent, visual cues like photos become essential tools for sellers to convey product quality to potential buyers. This reliance on visual information is significant in the consumer evaluation process. Xu, Zeng and He (2017) and Mugge *et al.* (2018) emphasize the critical impact of images on consumer perceptions of product quality. Kauffman and Wood (2006) further note that consumers are often willing to pay a premium for listings that provide rich, informative visual content. Multiple images not only give a comprehensive view of the remanufactured product but also signal the seller's commitment to transparency, enhancing their credibility. This, in turn, positively affects buyers' perceptions of quality, a finding corroborated by Stern and Stafford (2006) and Van der Heide, Johnson and Vang (2013).

The number of product images has been widely recognized as an indicator of quality, with research from Stern and Stafford (2006), Frota Neto, Bloemhof and Corbett, (2016), Xu, Zeng and He (2017), and Van Nguyen *et al.* (2020) demonstrates that listings with more images are more likely to be viewed as trustworthy and valuable, especially in auction settings where buyers rely heavily on visual information. Building on this, this study considers the number of images provided with each listing as a key factor influencing the auction price of remanufactured products. By systematically counting the number of pictures uploaded to each eBay listing, the study quantitatively examines how the visual cue impacts buyer behaviour and auction outcomes. This analysis aims to provide deeper insights into the relationship between image quantity and consumer decision-making in the context of online auctions for remanufactured goods.

6) Sentiment of Item Description (*SENTI*)

This research examines the impact of textual content in eBay's 'Item description from seller' section on buyer purchasing decisions, focusing on how product descriptions serve as a key medium for sellers to communicate product quality. While product condition and the number of photographs are well-established factors influencing buyer behaviour, textual descriptions offer an additional layer of information that can shape perceptions of the product.

Prior studies, such as Van Heijst, Potharst and Van Wezel (2008), highlight that the content of these descriptions can significantly affect auction outcomes, often having a greater impact than seller ratings alone. Frota Neto, Bloemhof and Corbett (2016) further explored this by investigating the effects of positively framed product descriptions on iPod prices, though their

findings were inconclusive regarding the direct impact of positive descriptions. Similarly, Van Nguyen *et al.* (2020) found that the positivity in descriptions had a moderate effect on perceived product quality for technological remanufactured products.

Building on this existing literature, this study takes a different approach by using advanced sentiment analysis techniques from Natural Language Processing (NLP) to analyse the sentiment within product descriptions (e.g., Van Nguyen *et al.*, 2020). Rather than simply counting positive keywords, as done in previous studies (e.g., Frota Neto, Bloemhof and Corbett, 2016), this research analyses the nuanced tone and depth of information conveyed through the seller's narrative to better understand how these textual elements influence buyer behaviour and decision-making. This approach aims to offer a more comprehensive understanding of how product descriptions contribute to auction outcome.

- **Buyer-side variables**

Buyer-side information refers to information produced by buyers in the context of information asymmetry and signalling theory in online commerce. These include customer reviews, seller ratings, feedback, and bidder engagement with the auction. By analysing these variables, this study aims to assess how buyer feedback and perspectives help to diminish information asymmetry, ultimately fostering a more transparent and trustworthy online marketplace.

By sharing their experiences, opinions, and feedback, buyers contribute to increasing transparency, trust, and decision-making in online commerce. Customer reviews, ratings, opinions, and recommendations are examples of various ways buyers can provide information. Other buyers can use these user-side signals as an important source of information to make

decisions. Potential customers can leverage buyer-generated information to gain a more thorough understanding of a product's quality, performance, and suitability for their needs, thereby reducing information asymmetry. It can also be an opportunity for sellers to change their sales strategies to a better one by receiving feedback on prices or products/services.

7) Number of Bidders (*BIDR*)

The number of bidders (*BIDR*) in an auction, reflecting total participant engagement, is a critical variable examined in this study to assess its impact on auction end prices. Research consistently demonstrates that a higher *BIDR* intensifies competition, often leading to overbidding, where participants bid beyond an item's rational estimated value, sometimes resulting in a "winner's curse" scenario (Ariely and Simonson, 2003; Suter and Hardesty, 2005; Cooper and Fang, 2008; Hou, Kuzma and Kuzma, 2009; Liang, 2014; Feng, Fay and Sivakumar, 2016; Hatamoto *et al.*, 2021; Ockenfels, Reiley and Sadrieh, 2006; Kim *et al.*, 2019).

This study leverages the common value auction model, where each bidder's valuation is influenced by collective signals within the auction environment (Milgrom and Weber, 1982; Ockenfels, Reiley and Sadrieh, 2006). As the *BIDR* increases, so does the competition, driving final prices higher. Late entrants often interpret the number of bids as an indicator of the item's value, leading to dynamic reassessment, where bidders adjust their valuations based on competitors' actions (Kamins, Dreze and Folkes, 2004; Ockenfels, Reiley and Sadrieh, 2006). Kauffman and Wood (2006) describe herd behaviour in auctions, where perceived interest from other bidders raises the WTP. Similarly, Liu, Wei and Chen (2010) identify the observational learning effect, where bidders adapt their bids in response to others, thereby escalating the

bidding intensity. Liang (2014) and Suter and Hardesty (2005) further explain that bids from others provide valuable information, prompting bidders to reassess the item's worth.

By exploring these dynamics, the study underscores the complexity of bidding behaviour, shaped by both individual decision-making and collective signals within the auction environment. The number of bidders emerges as a significant factor influencing auction outcomes, highlighting the crucial role of psychological and situational cues in shaping competitive auction landscapes.

8) Number of Bids (*BIDS*)

The “Number of Bids” (*BIDS*) is a critical factor influencing auction outcomes, particularly in terms of final prices, as it reflects the level of bidder engagement and the intensity of competition. Research by Highfill and O’Brien (2007) demonstrated a positive correlation between the number of bids and the final auction price in the context of art sales on eBay. Similarly, Bapna *et al.* (2004) identified *BIDS* as one of three strategic dimensions, alongside the time of entry and time of exit, that define bidder behaviour in auctions. Specifically, *BIDS* quantifies how frequently a bidder updates their offers, directly indicating their involvement and commitment to securing the auctioned item.

A higher *BIDS* often reflects greater perceived value by bidders, as frequent bidding activity signals heightened interest and determination. Additionally, *BIDS* serves as a proxy for the overall bidding cost, encompassing the time, effort, and other resources expended by participants. Bidders facing higher participation costs in terms of time or effort may bid less

frequently, highlighting the balance between engagement and the perceived value of the auctioned item.

However, one notable issue with *BIDS* is its strong correlation with the number of bidders, which can lead to multicollinearity in statistical models. Elhadary (2012) found a strong relationship between these two variables, noting that an increase in the number of bidders generally results in more bids. This presents a challenge in determining which variable—*BIDS* or *BIDR*—has a more significant impact on final prices. To address potential multicollinearity, it becomes essential to select the variable with the greatest explanatory power, ensuring the accuracy of the auction pricing model.

9) Average Time of Entry (*A_ENT*)

Bapna *et al.* (2004, 2009) also shed light on a crucial strategic variable known as “Time of Entry (*TOE*)” in the context of bidder’s strategy in online auctions. This variable signifies the specific moment when a bidder opts to join an auction, and it wields a direct influence over both bidder participation levels and the pricing dynamics of the auction. Elhadary (2012) discovered that the timing of the first bid plays a critical role in influencing auction outcomes, noting that earlier bids tend to increase both the number of bidders and subsequent bids.

Muthitacharoen and Tams (2017) extend the auction participant classification by Bapna *et al.* (2004), finding that shorter auctions increase the success probabilities for early bidders, termed Evaluators, while longer auctions favour Opportunists who enter late. This is attributed to Opportunists having more time to observe and react to other bidders in longer auctions.

Consequently, this study includes the timing of bid participation as a variable to analyse strategies of different bidder types effectively.

Given the variance in auction durations, the average entry time of participants is normalized to a scale from 0 to 1, representing it as a percentage of the total auction duration. For instance, entering a 5-day auction after 2 days and 1 hour equates to a normalized entry time of 0.4083, calculated by converting the total auction duration and the entry time into minutes (7200 and 2940 minutes respectively) and expressing this as a ratio. This method allows for consistent comparison and analysis across auctions of different lengths, helping to elucidate how timing influences auction dynamics.

10) Average Time of Exit (A_EXT)

Expanding upon the foundational work on bidder engagement, the “Average Time of Exit” (A_EXT) metric emerges as a pivotal aspect of understanding when bidders place their last bid or decide to exit an auction. This concept, building on the research by Bapna *et al.* (2004, 2009) and Chang (2012), further explores bidding behaviour through the lens of the “Time of Exit (TOX)” variable. By applying the same calculation method used for the “Average Time of Entry” (A_ENT), A_EXT offers a holistic perspective on bidders’ strategies, encapsulating both their entrance and departure from the auction. This dual-focused approach deepens the insights into how the timing of bids, not only at the start but also at the conclusion, affects the auction’s dynamics and final results, providing a richer understanding of auction engagement patterns (Bapna *et al.*, 2004).

11) Median of Bidder's Feedback score (M_{FEED})

Research has consistently demonstrated that bidder experience plays a crucial role in shaping bidding behaviours in auctions. For example, Livingston (2010) shows that experienced bidders on eBay adapt their strategies based on the seller's reputation and often engage in sniping, placing bids closer to the auction's end. Srinivasan and Wang (2010) found that seasoned buyers are more likely to secure homogeneous products at lower prices than their less experienced peers, a trend that Kostandini *et al.* (2011) confirm, noting that experienced bidders generally pay less than newcomers in online auctions for similar products. This consistency in bidding patterns supports earlier research and reflects traditional offline auction behaviours, where more experienced bidders also tend to achieve lower winning bids, as identified by Pownall and Wolk (2013).

Moreover, Feng, Fay and Sivakumar (2016) observed that both the frequency and magnitude of overbidding decrease as bidders gain experience and face higher auction stakes. Simonsohn and Ariely (2008) add that experienced bidders on eBay are less likely to be influenced by non-salient starting prices and less prone to herding behaviours that can lead to suboptimal decisions. In their study, Ow *et al.* (2018) highlight a nonmonotonic relationship between bidder experience and bid levels in online auctions: initially, inexperienced bidders place lower bids due to low trust. As they gain experience and trust, their bids increase, but as they become more skilled at evaluating value and identifying bargains, their bid amounts start to decrease again. This evolution in bidding behaviour underscores the complex impact of experience on auction dynamics, where gaining experience leads to more strategic and often more conservative bidding over time.

Building on these insights, this study employs the bidder's feedback score, accumulated through transactions, as an indicator of experience, much like the previously examined variable of seller's reputation. This feedback score has been chosen as a crucial variable to assess its impact on the final auction price. Reflecting the dynamic nature of auction bidding as seen in the work of Bapna, Jank and Shmueli (2008), which used average bidder experience as a determinant of auction price formation, this study also acknowledges that auction prices are influenced by the collective experience of bidders. To address data issues with extreme values in feedback scores, a median value calculation and log transformation were applied to control the distribution problem, aligning with methods used by Bapna, Jank and Shmueli (2008).

- **Platform-side variables**

Beyond the typical market signals arising from buyers and sellers, this study also incorporates institution-related variables to address broader aspects of online market environments. By integrating these variables, the research aims to capture a more comprehensive picture of the market, encompassing interpersonal interactions and platform-level influences. Institution-related factors are critical for understanding how structural aspects of the platform and historical data influence consumer decisions and enhance market transparency in online auctions.

In traditional settings like brick-and-mortar stores, consumers directly compare product quality, price, and other features. In contrast, online marketplaces such as eBay offer detailed and holistic insights, providing a complex perspective on market dynamics. This depth of information is possible because platforms like eBay retain sales data for three months after transactions, offering a rich dataset for analysing trends, buyer behaviour, and market dynamics.

Online shoppers have the valuable opportunity to glean insights from past sales data, enhancing their understanding of previous buyers' purchasing behaviours and tendencies.

12) Competitive Auctions (*COMP_AUC*)

Online concurrent auctions are not isolated events but interdependent, significantly impacting bidder behaviour and auction outcomes. In these auctions, multiple substitutable goods are offered concurrently across different platforms, allowing bidders to participate in several auctions simultaneously. This setup leads to overlapping auctions, where identical items are auctioned off simultaneously in a shared time interval, creating a complex market dynamic.

Empirical evidence from eBay supports the competing auctions theory, as revealed by Anwar, McMillan and Zheng (2006). They found that many bidders participate across multiple auctions, often choosing those with the lowest current bids, allowing cross-bidders to generally secure lower prices. Chan, Kadiyali and Park (2007) observed that in Korean laptop auctions, WTP decreases when similar items are listed concurrently, especially if they are of the same brand, highlighting the impact of market thickness. Bapna *et al.* (2009) found that overlapping auctions draw institutional bidders who typically depress auction prices. These bidders exert more significant downward pressure when they have information on forthcoming auctions compared to past auctions. Newberry (2015) determined that adding just one competitor in eBay Motors reduces the final price by 6%. Zhuang and Popkowski Leszczyc (2022) further explored how overlapping auction mechanisms affect revenue. They assessed the impacts of bidder behaviours such as learning, entry and withdrawal, forward-looking actions and time discounting, establishing optimal conditions for using sequential, simultaneous, or partially overlapping auctions to maximize outcomes.

In this study, this study operationalizes the concept of market thickness as the number of auctions for products within the same category that are available for bidding during the auction period of the focal product. Specifically, this study calculates the number of duplicate products based on those that are in overlapping time periods with the focal auction listing. Zhuang and Popkowski Leszczyc (2022) provide a framework that encompasses both fully overlapping and partially overlapping auctions. This approach allows us to examine how simultaneous auctions and the quantity of partially overlapping auction products in the same category influence auction outcomes. Through this analysis, this study gain insights into the dynamics of auction competition and its effects on final prices and bidder behaviour.

13) Historical Sales (*HIST_SALE*)

This study builds on foundational insights from prior studies, emphasizing the pivotal role of historical auction results in market dynamics. Auctions are interconnected, with the outcomes of previous ones influencing buyer perceptions and behaviours.

Chen, Wang and Xie (2011) explored how observational learning from historical sales impacts consumer decisions, finding that a positive sales history significantly boosts product sales, while negative data has minimal impact. Expanding these insights, Ye, Cheng and Fang (2013) demonstrated that products with strong historical sales in online marketplaces like eBay and Taobao tend to attract more future sales, as buyers often view past sales as indicators of quality and seller reliability. Xie, Mao and Wu (2019) further examined how transparency in sales history affects consumer behaviour on peer-to-peer rental platforms, discovering that clear transaction histories enhance purchases and diminish the negative effects of multiple listings. Most recently, Liu and Popkowski Leszczyc (2023) investigated how historical price lists affect

auction ending prices, finding that extensive price lists increase final auction prices by improving price transparency, especially for search goods. These studies collectively highlight the significant influence of historical sales data on shaping current and future auction outcomes.

In this study, historical sales records are identified as a key variable influencing the final price of remanufactured products. This study aggregate purchase records from various sellers within each product category, focusing on the comprehensive acquisition of transaction data rather than individual seller performance. By classifying data by product category rather than individual products, this study can conduct a broader analysis with more inclusive variables. This approach is particularly suitable for platforms like eBay, where sales records are available for 90 days. The *HIST_SALE* counts items sold in the same product category during the 90 days prior to a product's listing, providing a snapshot of recent market trends and pricing influences.

4.2.3 Data Exploration

Descriptive statistics are essential for establishing a foundational understanding of a dataset, offering key insights into variable distribution, central tendencies, and overall variability. In this study, a comprehensive statistical measure has been computed for each feature, including mean, and median, standard deviation, range and quartiles. These statistics facilitate the identification of patterns, inconsistencies, and potential outliers, thereby guiding subsequent data processing and modelling strategies.

Table 4.1 presents the descriptive statistics for the original dataset, which consists of 1039 complete observations with no missing values. All variables are in numerical form, either integer or float and relate to auction-specific dynamics, including starting price, competition

intensity, historical sales, sentiment analysis, item condition, listing duration, and participant behaviour (bidders and bids). The summary includes standard indicators such as minimum, maximum, mean and standard deviation, offering a structured overview of the dataset.

Table 4.1: Descriptive Statistics for the Original Dataset

Variables	Observations (n= 1039)						
	mean	std	min	25%	50%	75%	max
Starting Price	44.895	116.662	0.01	0.99	0.99	41.39	1231.8
Number of Competitive Auctions	26.654	24.481	0	9	19	36	139
Historical sales	178.271	205.480	0	25.5	83	250	785
Sentiment Score	0.547	0.143	0.278	0.438	0.557	0.621	0.9138
Number of Pictures	8.72	3.478	1	6	9	11	19
Condition	2.05	0.874	1	1	2	3	4
Duration	4.99	2.709	1	3	7	7	10
Number of Bids	23.69	17.069	1	8	23	37	83
Number of Bidders	9.686	6.241	1	4	9	14	33
Median Feedback Score of Bidders	226.296	681.141	0	25	93	235.5	16884
Average Entry Time	0.598	0.232	0	0.429	0.571	0.753	1
Average Exit Time	0.664	0.214	0	0.512	0.652	0.829	1
Total Feedback Score	42465.885	69252.012	228	679	18094	71396.5	310649
Feedback Score for 1 month	274.259	305.90	2	64	92	642	1114
Feedback Score for 6 months	1782.545	2007.003	19	382	608	4027	6897
Feedback Score for 12 months	3015.154	3466.275	49	475	1157	7425	13103

The starting price (mean = 44.90) spans a wide range from 0.01 to 1231.8, reflecting substantial variation in sellers' pricing strategies and the presence of extreme values. Competitive auctions average 26.65 per listing, with some cases experiencing up to 139 concurrent listings, indicating variability in market saturation. Historical sales (mean = 178) also exhibit a broad range, pointing to differing levels of seller experience and item popularity. The sentiment score of item descriptions is relatively consistent, with a mean of 0.55 and a moderate spread, suggesting overall neutral to positive sentiment. The number of pictures included in listings averages 8.7, while item condition is scored from 1 (Good) to 4 (Certified), averaging 2.05. Auction duration varies between 1 and 10 days, with an average of 5 days.

Bidding-related variables also reveal notable patterns. Each auction receives an average of 23.7 bids from approximately 9.7 bidders. The median feedback score of bidders (mean = 226) shows significant dispersion, with a maximum value exceeding 16,800, highlighting variation in bidder experience. Entry and exit times of bidders tend to cluster around 60% and 66% of the auction duration, respectively, suggesting that bidding activity intensifies in the later stages. Seller performance metrics are particularly skewed. The total feedback score (mean = 42,466) reaches as high as 310,000 in some cases, indicating a small number of highly experienced sellers. Recent feedback metrics over 1, 6, and 12 months also display wide variability, with averages of 274, 1,782, and 3,015 respectively, reflecting fluctuations in recent seller activity.

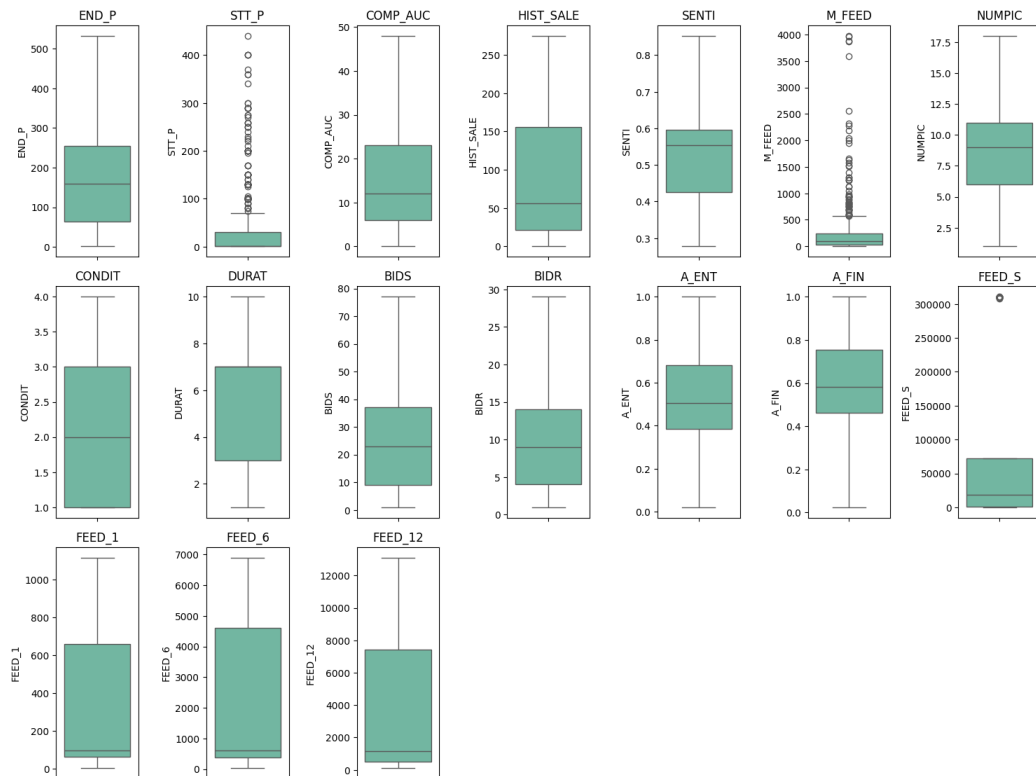


Figure 4.2: Box Plots Showing Distribution of the Original Dataset

Importantly, as shown in **Figure 4.2**, several variables, particularly *STT_P*, *M_FEED*, and *FEED_S*, exhibit strong right-skewed distributions and contain numerous outliers. These distributional characteristics necessitate careful consideration during the preprocessing phase, including potential log transformations or robust scaling techniques, to mitigate distortion in model training and ensure analytical reliability.

4.3 Data Preparation

This section outlines the essential steps of data preparation, focusing on four key stages: data cleaning, construction, feature selection, and scaling. These stages are crucial for ensuring the accuracy and reliability of the dataset, which serves as the foundation for meaningful analysis. Each phase addresses specific challenges, such as errors, outliers and missing values, that could otherwise compromise the validity of the study. By systematically organizing and refining the data, the preparation process resolves potential issues that may affect the analysis, such as data quality and relevance. This structured approach not only enhances the robustness of the dataset but also ensures that it is well-suited for the in-depth examination and insights to follow.

4.3.1 Data Cleansing

To ensure the accuracy and reliability of the dataset, a series of targeted measures were undertaken—centred on data cleansing—to mitigate issues such as errors, outliers and missing values that could compromise the validity of the study’s results. This phase included correcting data entry errors, handling missing values, and managing outliers that might skew the analysis. Through execution of data cleansing is essential for producing robust research outcomes.

- **Errors**

In this study, special attention was given to feedback scores, where 18 entries were marked as “private”, indicating that some users opted not to disclose their scores. To resolve the issue, the study employed an imputation method, replacing the ‘private’ feedback entries with the median feedback score. This approach ensured that the dataset remained complete and that potential biases or inaccuracies stemming from missing information were minimized. By imputing the median score in the skewed distribution, the feedback variable remained meaningful and comparable across all data points, supporting a robust and valid analysis. This step was crucial in ensuring the integrity and reliability of the feedback scores in the overall dataset.

- **Outliers**

Outliers can significantly distort analytical outcomes, particularly in regression models. To enhance the integrity of the dataset and improve the robustness of the analysis, a systematic approach was applied to detect and remove such anomalies. Specifically, data points lying beyond the 3-sigma range from the mean were excluded, and boxplots based on the 1.5 * interquartile range (IQR) rule were used to visually confirm the presence of extreme values. As a result of this process, 100 outliers were removed, reducing the risk of distortion and enhancing the reliability of the dataset. However, certain variables, such as *STT_P*, *M_FEED* and *FEED_S*, still exhibited highly skewed distributions. These variables were subsequently addressed through data transformation to ensure analytical completeness.

- **Missing value**

The presence of missing values degrades statistical performance, complicates data analysis, and leads to biased results (Ayilara *et al.*, 2019). Missing data can stem from various sources, including data entry errors or technical issues in data collection systems. However, a thorough examination of the dataset confirmed that there are no missing values in the dataset, as detailed in **Table 4.1**. The absence of missing values enhances the reliability of the dataset, supporting a more straightforward analytical process and bolstering confidence in the accuracy and robustness of the research findings.

4.3.2 Data Construction

The Data Construction section focuses on the creation and refinement of the dataset by producing derived attributes, generating new records, and transforming existing values. By constructing new attributes and refining the existing data, this stage lays a strong foundation for the subsequent analytical processes. Derived attributes are generated to capture more complex relationships within the data, while new records are created to fill gaps or provide additional context. Additionally, transformations of existing values are performed to standardize and align the data with the study's objectives, ensuring that the dataset is comprehensive and tailored for the analysis ahead.

This process is divided into two distinct parts for structured and unstructured data. This dual approach ensures that both data types are appropriately processed and integrated. By systematically handling each type, the process produces a comprehensive dataset that aligns with the study's objectives and is suitably prepared for subsequent procedures.

4.3.2.1 Structured Data

- **Encoding**

To convert categorical data into numerical format, two common methods are ordinal encoding and one-hot encoding. Ordinal encoding is ideal for variables with a natural ranking, as it assigns numerical values that reflect their order. In this study, the conditions for remanufactured products—Good, Very Good, Excellent, and Certified—is encoded from 1 to 4. This approach preserves the ordinal nature of the variable, ensuring that the inherent order is maintained for more accurate analysis and interpretation.

- **Data Transformation (Log Transformation)**

Data transformation is another critical step in data preparation, aiming to stabilize variance, normalize distributions, and reduce the influence of outliers. These transformations are essential for improving data normality and meeting the assumptions required for accurate statistical analysis (Osborne, 2002). For variables exhibiting significant skewness or outliers, transformations like the logarithmic transformation help compress the data range, bringing extreme values closer to the mean and producing a more symmetrical distribution.

This step is particularly important for statistical models such as LR, which often assume normally distributed data. In this study, several key variables with skewed distributions—*STT_P*, *FEED_S*, and *M_FEED*—were log-transformed into *STT_P_ln*, *FEED_S_ln*, and *M_FEED_ln*, respectively. Through these transformations, the data were better aligned with the assumptions of the analytical models, thereby enhancing the robustness and reliability of the analysis. skewness and normalisation of key variables, the log transformations improve dataset quality, enabling more accurate analyses and supporting more robust conclusions.

4.3.2.2 Unstructured Data

Unstructured textual data, particularly seller-provided product descriptions, plays a critical role in shaping consumer behaviour and WTP (Van Heijst, Potharst and Van Wezel, 2008; Frota Neto, Bloemhof and Corbett, 2016; Van Nguyen *et al.*, 2020). These descriptions often serve to elaborate on product condition and specifications, functioning as key informational signals influencing buyer decision-making under uncertain conditions. While prior research has employed simple keyword frequency counts to assess the impact of textual content (Van Heijst, Potharst and Van Wezel, 2008; Frota Neto, Bloemhof and Corbett, 2016), the present study adopts a more sophisticated approach by examining the narrative quality of product listings using natural language processing techniques, as demonstrated by Van Nguyen *et al.* (2020). This method enables a deeper, context-aware analysis of seller-generated content and directly address the issue of information asymmetry in online auction environments.

- **Sentiment Analysis**

To analyse the sentiment embedded in unstructured item descriptions, this study utilizes the pre-trained “Bert-base-multilingual-uncased-sentiment” model from the Hugging Face BERT family. The sentiment scores generated by the BERT model are then integrated into the structured dataset as variables, enriching the analysis with insights drawn from the textual data. This integration allows a more comprehensive examination of how seller-generated signals—conveyed through product descriptions—influence auction outcomes. By moving beyond simple positivity analysis and employing advanced sentiment analysis techniques, this study offers a deeper understanding of the subtle aspects of customer sentiment and their impact on the demand prediction model for refurbished products.

4.3.3 Feature Selection

This step involves filtering out highly correlated or irrelevant data to streamline the dataset and improve analytical efficiency. By retaining only the most relevant variables, the study ensures that the dataset captures the essential information needed to generate meaningful and accurate conclusions.

Addressing multicollinearity is especially important before conducting an OLS regression, particularly when comparing LR models with non-linear ML methods. As indicated in **Table 4.2**, several variables show high correlations—most notably among feedback score-related variables (*FEED_S_In*, *FEED_1*, *FEED_6*, and *FEED_12*), the number of bids and bidders (*BIDS*, *BIDR*), and the average time of entry and exit of the bidders (*A_ENT*, *A_EXT*).

Table 4.2: Correlation Matrix for the Dataset Used in Analysis

	END_P	STT_P_In	COMP_AUC	HIST_SALE	SENTI	M_FEED_In	NUMPIC	CONDIT	DURAT	BIDS	BIDR	A_ENT	A_FIN	FEED_S_In	FEED_1	FEED_6
STT_P_In	-0.1625															
COMP_AUC	-0.0098	-0.1031														
HIST_SALE	0.3729	-0.3340	0.0443													
SENTI	0.3339	-0.2599	0.0195	0.1742												
M_FEED_In	-0.3379	0.2092	-0.1023	-0.2462	-0.1021											
NUMPIC	0.2942	-0.1092	0.0732	0.3942	-0.1466	-0.2280										
CONDIT	0.2543	-0.3118	-0.0716	0.2147	0.2148	-0.1360	-0.0506									
DURAT	-0.4359	0.3908	0.2110	-0.5329	-0.1267	0.3409	-0.4554	-0.2713								
BIDS	0.5208	-0.6754	0.1291	0.4021	0.3198	-0.4340	0.2532	0.2650	-0.4418							
BIDR	0.4864	-0.6510	0.1482	0.3622	0.2983	-0.3898	0.2513	0.2195	-0.3942	0.8825						
A_ENT	-0.3780	0.5883	-0.1128	-0.2649	-0.2409	0.3053	-0.1268	-0.2586	0.2955	-0.5717	-0.5157					
A_FIN	-0.4219	0.5792	-0.0885	-0.2844	-0.2669	0.3258	-0.1535	-0.2531	0.3054	-0.5740	-0.5737	0.9211				
FEED_S_In	-0.3207	0.3947	0.1329	-0.3610	-0.1678	0.3418	-0.1943	-0.4803	0.6485	-0.4094	-0.3719	0.2725	0.3060			
FEED_1	-0.4561	0.2905	0.2290	-0.3643	-0.4618	0.2746	-0.1356	-0.3681	0.5347	-0.3911	-0.3404	0.2272	0.2802	0.6924		
FEED_6	-0.4566	0.3047	0.2270	-0.3648	-0.4801	0.2706	-0.1186	-0.3953	0.5362	-0.4015	-0.3485	0.2256	0.2811	0.7024	0.9873	
FEED_12	-0.4438	0.2592	0.2566	-0.3421	-0.4316	0.2648	-0.1363	-0.3965	0.5208	-0.3628	-0.3138	0.1951	0.2567	0.7301	0.9790	0.9879

Table 4.3 reports the Variance Inflation Factors (VIFs), which provide further evidence of multicollinearity among several predictors. While high VIF values indicate potential redundancy and correlation between variables, they do not require immediate removal. Rather, they serve as diagnostic tools to inform more deliberate decisions regarding variable selection, transformation, or dimensionality reduction to enhance model stability and interpretability.

Table 4.3: Variance Inflation Factors for Each Variable

Feature	VIF
FEED_6	166.2367
FEED_12	118.5375
FEED_1	79.6105
A_FIN	69.8581
FEED_S_In	59.7290
A_ENT	53.7790
SENTI	24.8556
BIDR	18.3028
BIDS	17.6657
DURAT	12.4894
M_FEED_In	11.9711
NUMPIC	11.7205
CONDIT	7.1697
STT_P_In	5.5887
COMP_AUC	3.6857
HIST_SALE	3.5512

To address multicollinearity and reduce redundancy among highly correlated features, only one variable from each correlated group was retained. Feature selection was informed by the relative importance of variables, assessed using SHAP values derived from both RF and XGBoost models. As presented in **Table A.3 (Appendix)**, both RF and XGBoost models were evaluated under three train-test split ratios: 8:2, 7:3, and 6:4. Cross-validation and test set performance were compared across these configurations to identify the most robust data partitioning strategy.

Although the 7:3 split yielded marginally better R^2 , RMSE, and MAE scores during cross-validation, the 8:2 split demonstrated comparable performance and achieved superior predictive accuracy on the test set. To ensure that this result was not due to a particular random seed, the experiment was repeated using a different random state. As shown in **Table A.4**, the 8:2 split consistently achieved the highest performance metrics across both cross-validation and test sets, confirming its reliability and suitability for this study.

As illustrated in **Figure 4.3**, among the four feedback-related variables, *FEED_1* demonstrated the highest importance across all three evaluation metrics and was therefore retained, while the remaining three variables were excluded to avoid redundancy. A similar approach was applied to bidding-related features: *BIDS* was selected over *BIDR* due to its higher feature importance. For bidder activity measures, *A_ENT* was retained in favour of *A_EXT*, supported by both a lower VIF and stronger theoretical justification regarding its relevance to bidder engagement, as established by prior literature (Bapna *et al.*, 2009; Chang, 2014). Further examination of VIF values led to the exclusion of additional variables: *SENTI* was removed due to excessive multicollinearity, and *M_FEED_In* was dropped based on its high VIF and consistently low importance across all feature selection methods.

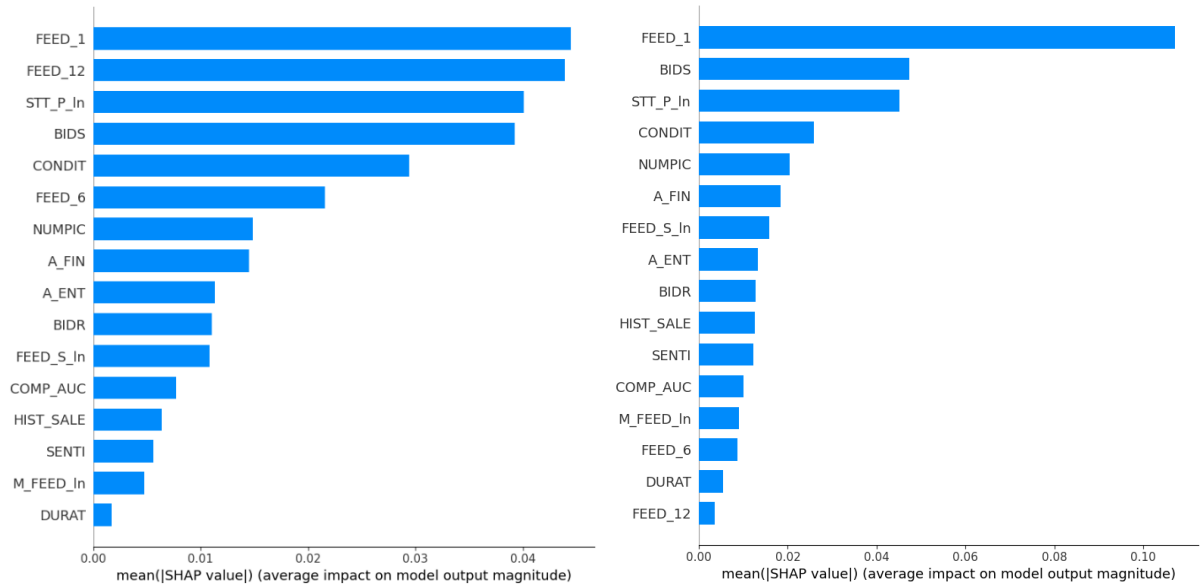


Figure 4.3: SHAP Summary Bar Plots of All Features for RF and XGBoost Models

The final VIF values, following the removal of multicollinear features and optimisation of variable selection, are presented in **Table 4.4**. All retained variables exhibit VIFs below the generously accepted threshold of 10. While more conservative cut-offs (e.g., $VIF < 5$ or < 3) are sometimes recommended to increase statistical precision, such thresholds may result in the exclusion of relevant predictors, thereby limiting the model's explanatory capacity. To maintain a balance between statistical robustness and interpretability, this study adopts the conventional threshold of $VIF < 10$.

Although multicollinearity is generally less problematic in ML algorithms, such as Ridge, Lasso and tree-based algorithms, due to their built-in regularisation or tolerance for correlated features, it remains a critical issue in OLS regression. In OLS, multicollinearity can inflate standard errors, distort coefficient estimates, and compromise the interpretability of the results. Therefore, VIF-based variable exclusion was specifically applied to enable valid comparisons with multicollinearity-sensitive models, particularly OLS regression. In contrast, for

regularised models and tree-based ML algorithms, a broader set of explanatory variables was retained to preserve analytical depth, capitalising on these models' ability to handle feature correlation. This approach aligns with the standards adopted in prior studies, such as Frota Neto, Bloemhof and Corbett (2016), Xu, Zeng and He (2017), and Van Nguyen *et al.* (2020), the latter of which also applied a $VIF < 10$ threshold in comparative modelling contexts.

Table 4.4: Variance Inflation Factors After Feature Elimination

Features	VIF
A_ENT	9.0422
NUMPIC	8.7929
DURAT	7.2599
CONDIT	5.6233-
BIDS	5.5084
STT_P_ln	4.8074
HIST_SALE	3.4208
COMP_AUC	3.3295
FEED_1	3.0263

4.3.4 Data Scaling

Data formatting is the final step in dataset preparation, where selected data is standardized and organized to ensure compatibility with advanced statistical and ML techniques. This step is crucial for aligning different units or scales across variables, allowing for accurate comparisons and analyses (Han, Kamber and Pei, 2012). Proper data formatting is essential to obtain reliable results, as inconsistencies in data scaling can lead to biased or inaccurate model outputs.

To address scaling differences, this study employs the MinMaxScaler, which adjusts each variable to a common range, typically between 0 and 1. This transformation rescales each feature to a defined range, preserving the relative relationships between data points. MinMax scaling is particularly effective for datasets with variables measured on diverse scales, ensuring

that each variable contributes equally to the analysis and minimizing potential biases (Patro and Sahu, 2015). This standardization provides a more accurate foundation for analysis, ultimately enhancing the clarity, interpretability, and robustness of the results.

4.4 Empirical Results

This section provides a comprehensive analysis of the empirical results obtained from the implementation of the proposed models. Through detailed examination and rigorous statistical procedures, the study seeks to uncover the underlying relationships, patterns, and trends within the dataset. The empirical findings presented here serve as the foundation for subsequent discussions and interpretations, ultimately contributing to a deeper understanding of the investigated phenomenon.

As shown in **Table 4.5**, which reports the descriptive statistics of the dataset before scaling, the average final price of the items is approximately £171.98, while the average starting price is £30.08 (not in transformed form), indicating that most auctions begin with relatively low initial prices. On average, each item receives around 15.07 bids, and items typically have a historical sales count of 87.92, reflecting substantial category-level transaction history. Sellers tend to provide 8.67 images per listing, offering considerable visual detail to potential buyers. The mean item condition score is 2.02, capturing a spectrum of product states. Auctions last an average of 4.88 days and attract about 23.59 bids, suggesting high buyer engagement. The average bidder entry point within the auction cycle is 0.55, and sellers have an average feedback score of 288.49, indicative of their reputation and trustworthiness.

Table 4.5: Descriptive Statistics After Feature Elimination

	Observations (n = 939)						
	mean	std	min	25%	50%	75%	max
END_P	171.9830	122.0059	1.7000	63.0000	160.0000	255.0000	532.0000
STT_P_In	1.8737	1.6740	0.6881	0.6881	0.6881	3.4337	6.0889
COMP_AUC	15.0745	11.5295	0.0000	6.0000	12.0000	23.0000	48.0000
HIST_SALE	87.9212	79.5978	0.0000	21.0000	56.0000	155.5000	275.0000
NUMPIC	8.6731	3.3563	1.0000	6.0000	9.0000	11.0000	18.0000
CONDIT	2.0245	0.8885	1.0000	1.0000	2.0000	3.0000	4.0000
DURAT	4.8829	2.7700	1.0000	3.0000	7.0000	7.0000	10.0000
BIDS	23.5900	16.5628	1.0000	9.0000	23.0000	37.0000	77.0000
A_ENT	0.5471	0.2256	0.0208	0.3835	0.5057	0.6814	1.0000
FEED_1	288.4867	310.0026	3.0000	64.0000	96.0000	659.5000	1114.0000

As previously discussed, RF and XGBoost were used as benchmark algorithms to determine the most suitable train–test split before proceeding with full-scale model implementation. Model performance was assessed under three partitioning scenarios: 80:20, 70:30, and 60:40. Although the 70:30 split yielded cross-validation scores comparable to those of the 80:20 split, the 80:20 configuration consistently produced superior results on the test set for both models (see **Table A.3**). To ensure the robustness of this outcome, the procedure was repeated with an alternative random seed. The 80:20 split continued to demonstrate the highest performance across both cross-validation and test sets, confirming its stability and reliability (**Table A.4**). Consequently, the 80:20 train-test ratio was adopted as the final data partitioning strategy for all subsequent modelling tasks.

Table 4.6 summarises the descriptive statistics and corresponding VIF values for each variable, based on the 80:20 train-test split. All VIF values remained below the threshold of 10, suggesting that multicollinearity was not a significant concern. All predictive models were trained exclusively on the training dataset and evaluated on the independent test dataset. To further mitigating resampling bias and support generalisability, 10-fold cross-validation with

three repetitions was employed throughout the modelling process (Van Nguyen *et al.*, 2020). This approach is consistent with established best practices in ML and statistical modelling, thereby enhancing the robustness, reliability, and credibility of the study's findings.

Table 4.6: Descriptive Statistics for the Training and Test Datasets

	Training dataset (N = 751 observations)					Testing dataset (N = 188 observations)				
	min	max	mean	std	VIF	min	max	mean	std	VIF
END_P	1.7	532	174.57	120.65	-	2.2	501	161.64	127.08	-
STT_P_In	0.69	6.09	1.82	1.653	5.11	0.69	5.99	2.10	1.74	4.24
COMP_AUC	0	48	15.46	11.703	3.43	0	47	13.53	10.70	3.07
HIST_SALE	0	275	89.59	79.014	3.43	0	271	81.26	81.76	3.55
NUMPIC	1	18	8.72	3.352	8.85	1	17	8.49	3.38	8.93
CONDIT	1	4	2.01	0.874	5.84	1	4	2.09	0.94	5.40
DURAT	1	10	4.82	2.797	7.22	1	10	5.14	2.65	7.64
BIDS	1	76	24.33	16.640	5.83	1	77	20.64	15.96	4.50

4.4.1 Evaluation of Predictive Model Performance

This study broadens the analytical scope by incorporating a more diverse set of six regression algorithms, enhancing the robustness of predictive performance and offering a more comprehensive perspective on the factors influencing auction prices for remanufactured products. This approach builds on prior efforts to mitigate modelling bias, such as those by Van Nguyen *et al.* (2020), who employed five different algorithms to predict customer demand for remanufactured products. In addition to the simple LR model, Ridge and Lasso models, which utilize regularization to manage issues like multicollinearity and overfitting, were introduced. The study also extends the framework of Van Nguyen *et al.* by adding XGBoost to the previously used models—CART, M5, and RF—thereby further strengthening the predictive power and reliability of the analysis.

Figure 4.4 presents the prediction results for both the training and testing phases, using boxplots to illustrate the distribution of each performance metric— R^2 , RMSE, and MAE—obtained through 10-fold cross-validation repeated three times. The black dot within the boxplots indicate the average performance during training, providing a measure of the model’s central tendency. Red dots represent performance on the test dataset. When these red dots fall within the interquartile range of the training distribution, it suggests that the model generalises well, showing no significant signs of underfitting or overfitting.

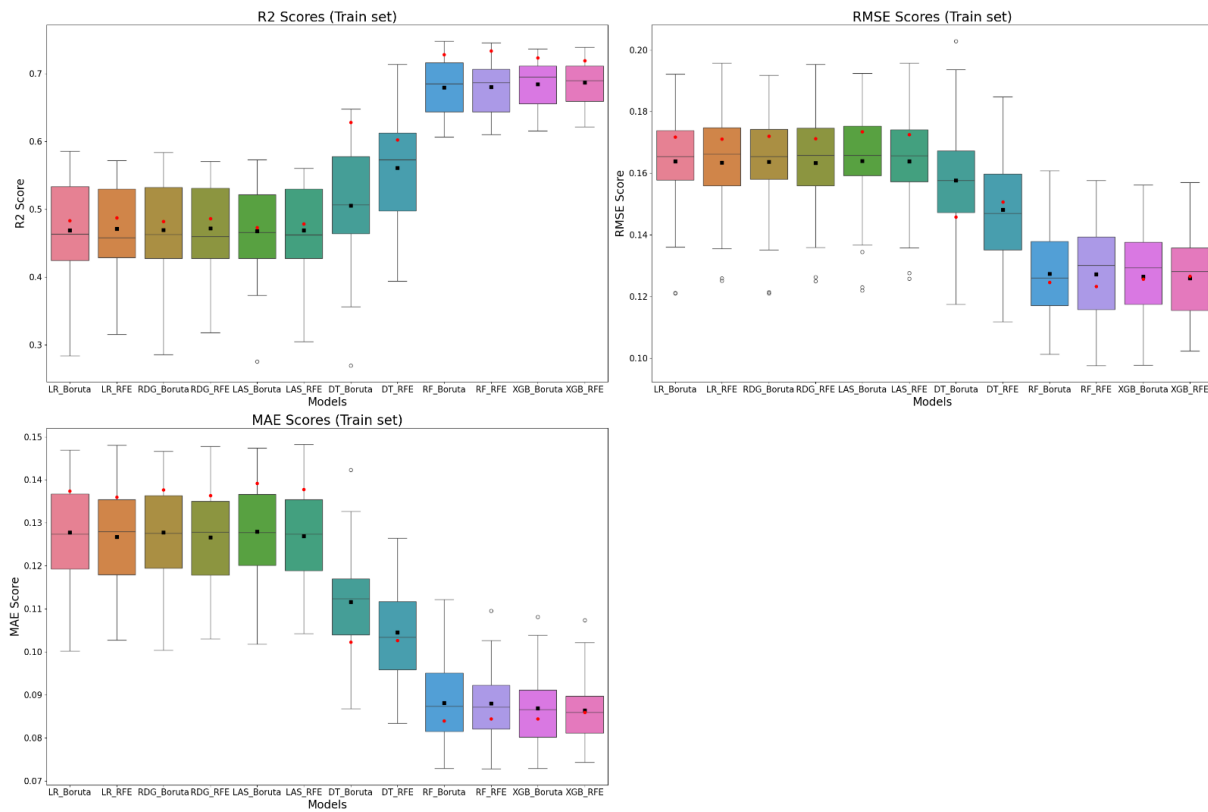


Figure 4.4: Predictive Performance of Models on Training and Testing Sets

The results in **Figure 4.4** highlight the superior predictive performance of ML methods across all metrics, reinforcing their suitability for modelling the complex, non-linear dynamics of auction prices for remanufactured products. These findings underscore the advantage of ML

algorithms, particularly those capable of capturing non-linear interactions, over conventional LR models in this context. Additionally, the figure reveals the impact of feature selection methods on model performance. Two ML models—RF and XGBoost—were further examined using RFE and Boruta to assess the impact of different variable selection strategies. While training results were relatively comparable across the four ML models, models such as *RF_RFE*, *XGB_RFE* and *XGB_Boruta* showed MAE values beyond the 1.5 interquartile range (IQR), indicating some deviation in model performance. On the other hand, the *RF_Boruta* model demonstrated robust performance, with no outliers across all three metrics and a close alignment between training and test performance, as evidenced by the proximity of its red and black dots.

Overall, the figure not only confirms the effectiveness of the ML methods in predicting auction outcomes but also underscores the importance of selecting appropriate feature selection techniques. Among the models, *RF_Boruta* delivered the most stable and superior results, establishing it as the most reliable approach for modelling consumer demand in online auctions for remanufactured products.

4.4.2 Model Deployment – Interpretation of Results

As part of the model deployment process, understanding the relative importance of features influencing auction outcomes is crucial for generating actionable managerial insights. To achieve SHAP was employed to evaluate and rank feature importance. As detailed in the Methodology section, SHAP values provide a consistent and theoretically grounded measure of each feature's contribution to a model's prediction by distributing the output across all features. This approach enhances interoperability and enables more informed, data-driven decision-making by clearly illustrating which factors drive auction performance.

4.4.2.1 Feature Importance

Following the identification of the RF combined with Boruta as the best-performing configuration, a detailed analysis of feature importance was conducted. This section focuses on the most impactful variables identified through SHAP analysis of the *RF_Boruta* model.

Figure 4.5 presents the average absolute SHAP values in a summary bar chart format, with features ranked along the x-axis by their relative importance. These values reflect the average magnitude of each feature's contribution to the predicted final auction price across all instances. The top five most influential features are *FEED_1*, *BIDS*, *STT_P_In*, *NUMPIC*, *A_ENT*. Specifically, the estimated average contribution (in £GBP) of each to the predicted auction price is as follows: *FEED_1* (± 36.79), *BIDS* (± 27.78), *STT_P_In* (± 19.45), *NUMPIC* (± 16.02), *A_ENT* (± 13.17) and *CONDIT* (± 11.61). In contrast, variables such as *HIS_SALE*, *DURAT* and *COMP_AUC* had relatively lower impacts on prediction outcomes.

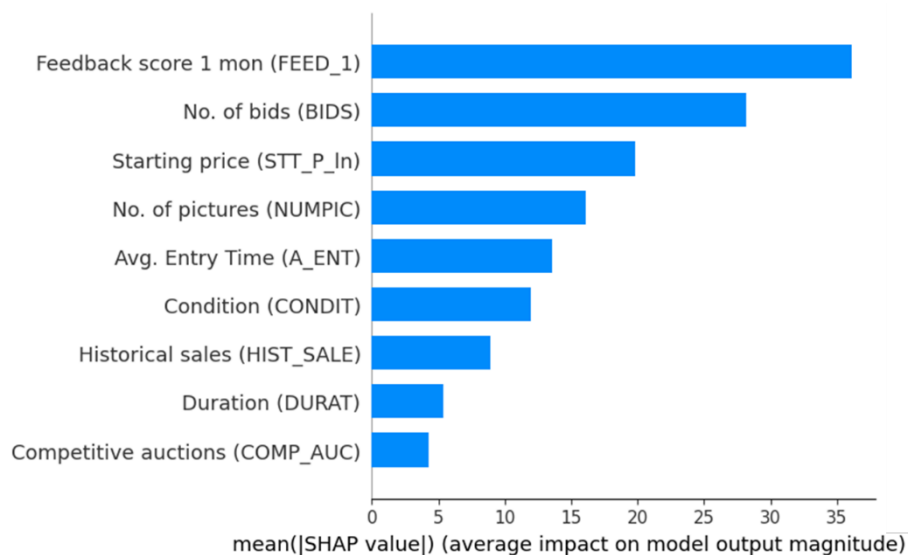


Figure 4.5: SHAP Summary Bar Plot for the *RF_Boruta* Model

Figure 4.6 provides a SHAP beeswarm summary plot, offering a more granular view of how individual feature values affect predictions. The y-axis lists the features observed by importance, while the x-axis displays SHAP values indicating the direction and magnitude of each variable's impact. Each point represents a data instance, coloured by the corresponding feature values—red indicating higher values and blue indicating lower ones. The width of the plot (i.e., the spread along the x-axis) reflects the variability of the feature's impact on the target variable.

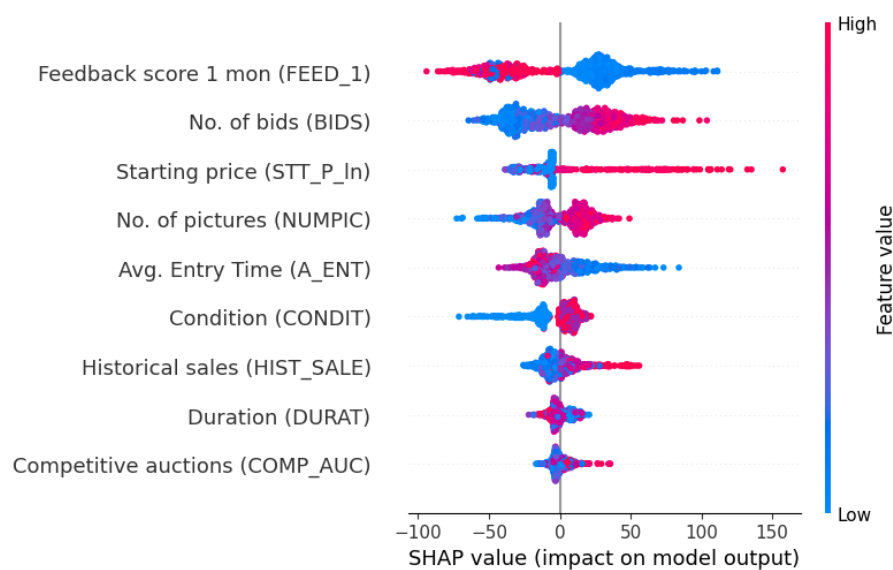


Figure 4.6: SHAP Beeswarm Summary Plot for the *RF_Boruta* Model

A key observation from **Figure 4.6** is that lower seller feedback scores (*FEED_1*) contributed to higher final auction prices, whereas higher *FEED_1* values are linked to a lower final auction price. This finding runs counter to prior literature, which typically associates strong feedback with increased buyer trust and higher prices. This finding is counterintuitive as most existing literature suggests that better feedback correlates with higher auction end prices. This finding suggests that on platforms like eBay, where the feedback score is tied to the seller's experience, sellers sold smaller quantities or newer sellers often have lower scores compared to more

established sellers (e.g., Che *et al.*, 2019; Hui *et al.*, 2016). This prompts further investigation into the marginal effect between *FEED_1* and the end auction price in later analysis.

Other variables follow expected patterns: higher numbers of bids, higher starting prices, more pictures, better item conditions, earlier bidder entry (lower *A_ENT*), as well as greater historical sales and competition from simultaneous auctions, all correlate positively with final auction prices. These patterns are consistent with established findings in the auction and e-commerce literature. Further analysis on the marginal effects of these variables, particularly *FEED_1*, will be presented in subsequent sections to explore these dynamics in greater depth.

4.4.2.2 SHAP Dependence Plots and Interaction Analysis

Figure 4.7 presents the SHAP dependence plots, which illustrate how changes in individual feature values on the x-axis and their corresponding SHAP values on the y-axis, with histograms along the x-axis showing the distribution of each variable. A SHAP value above zero indicates a positive contribution to the predicted end price, whereas a value below zero suggests a negative contribution (Lundberg and Lee, 2017). The diverse shapes of the dependence plots reflect complex, often non-linear relationships—an area where explainable ML models excel compared to traditional LR models.

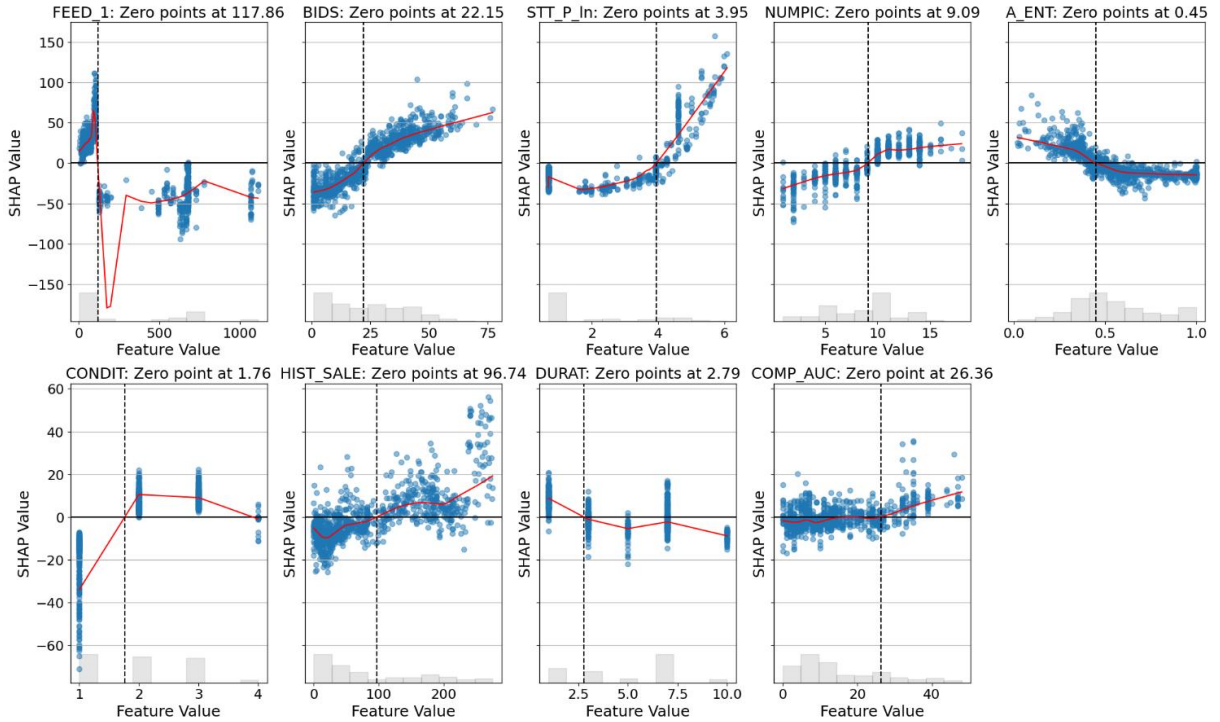


Figure 4.7: SHAP Dependence Plots for the *RF_Boruta* Model

1) Feedback score for the last 1 month (*FEED_1*)

The PDP for *FEED_1* reveals a significant threshold at 117.86, dividing the data into two distinct seller groups. Below this value, accounting for 59.1% of the dataset feedback is positively associated with higher auction prices, typically representing private or less experienced sellers. Above this threshold, feedback scores are negatively associated with the end prices. The observed differences are likely attributable to distinct sales strategies adopted by sellers at varying levels of experience. As noted by Chen, Lai and Yu (2018), auction formats typically involve shorter selling durations and result in lower prices compared to fixed-price listings, which allow more time and generally achieve higher sale values. In this dataset, less experienced sellers tended to favour shorter auction periods, averaging approximately 3.44 days, to expedite transactions, accumulate feedback, and establish a sales history, even at the expense of lower final prices. Notably, they also sold relatively higher-condition products (average

condition rating of 2.3), likely as a compensatory strategy to mitigate the disadvantage of lower feedback scores. In contrast, more experienced sellers adopted longer auction durations, averaging 6.96 days, and offered lower-condition products (average condition rating of 1.65). These sellers often diversify their sales strategies by combining auction and fixed-price listings, using auctions as a channel to quickly move lower-quality remanufactured items. Such strategic differences in product quality, listing duration, and channel selection contribute to the variation in final prices observed across different seller segments.

2) Number of bids (*BIDS*)

The *BIDS* plot exhibits a positive relationship with the final price and displays a thick vertical distribution, which indicates the increase by interaction with other variables in a fixed value of variable. A clear inflection occurs at 22.15 bids. Below this value, *BIDS* has a negative influence on the predicted price; above it, the effect turns positive. This suggests that only when competition reaches a certain intensity does it begin to raise the auction price significantly. This aligns with findings by Ariely and Simonson (2003) and Highfill and O'Brien (2007), who reported that greater *BIDS* lead to higher final prices provided a critical mass is reached.

3) Starting Price (*STT_P_ln*)

The log-transformed starting price (*STT_P_ln*) plays a significant role in influencing model's predictions. Generally, as *STT_P_ln* increases, its impact on the predicted end price is positive. The analysis reveals a key threshold at approximately 3.95 ($\approx$ £51). Below this point, it tends to have a negative effect on the majority of predictions, suggesting that lower starting prices might be perceived as indicative of lower value to bidders. Once this threshold is surpassed, the effect becomes positive indicating that higher starting prices enhancing buyer perceptions and

ultimately increase final auction outcomes. This pattern is consistent with research by Ariely and Simonson (2003), Brint (2003), Liang and Chen (2012), Liang (2014); Stern and Stafford (2006), all of whom observed that higher starting prices serve as an effective quality signal for the model's predictions in auction contexts.

4) Number of pictures (*NUMPIC*)

NUMPIC exhibits a generally positive correlation with the final auction price, suggesting that more images can enhance perceived value. The most significant gains occur between 8 and 11 images. Below 9.09, SHAP values are predominantly negative, indicating that fewer pictures may reduce buyer confidence or interest, adversely affecting the auction price. As *NUMPIC* exceeds this point, the impact shifts positively, contributing to higher auction prices. This pattern suggests that an increased *NUMPIC* effectively communicates more information about the product, enhancing buyer trust and perceived value. Interestingly, the positive impact of adding more images levels off after 11 pictures, possibly due to information overload. Lee and Lee (2004) argued that too much information can overwhelm buyer and hinder decision-making. This finding is supported by various research (e.g., Hou, 2007b; Stern and Stafford, 2006; Van der Heide, Johnson and Vang, 2013; Xu, Zeng and He, 2017), that a higher *NUMPIC* serves as a strong positive indicator for final auction prices, up to a certain point.

5) Average entry time (*A_ENT*)

Figure 4.7 shows that the average dates of entry (*A_ENT*) into a bid have a varied impact on the predicted end price in an auction. When *A_ENT* is less than 0.45, it generally contributes positively to most predictions, effectively increasing the predicted outcome. This reflects a scenario where bidders who enter the auction at an earlier stage tend to drive the end price

higher. In contract, as A_ENT values increase beyond 0.45, their association with the end price becomes negative suggesting that later entry by bidders typically depresses the final auction price. This observed behaviour aligns with findings from previous research (Elhadary, 2012, Li, Srinivasan and Sun, 2009; Stern and Stattford, 2006), which support the notion that earlier participation in bidding ($A_ENT < 0.45$) can lead to higher end prices. Notably, the influence of A_ENT on auction outcomes diminishes when its values exceed 0.6 at which point it appears to have a negligible effect on the price, neither increasing nor decreasing it significantly. This indicates that there is a threshold in the timing of entry beyond which the effect on price stabilizes, providing a comprehensive insight into bidder behaviour and auction dynamics.

6) Condition (*CONDIT*)

The relationship between the condition of a product and its final auction price is illustrated by the variable *CONDIT*, where a rating of 1 corresponds to a Good condition. As expected, a lower product condition is linked to a lower end price. As the product condition improves, moving through ratings 2 (Very Good), 3 (Excellent), and 4 (Certified-Refurbished), the impact on the auction price becomes increasingly positive. Specifically, when *CONDIT* falls below 1.76, it has a negative impact on the model's predictions, leading to a decrease in the end price. However, once *CONDIT* rises above 1.76, its influence becomes positive, actively driving the end price upward. This pattern indicates that higher *CONDIT* values, which represent better product conditions, are associated with higher end prices, as supported by research from Makov *et al.* (2019), Frota Neto, Bloemhof and Corbett (2016), and Xu, Zeng and He (2017). Interestingly, while all conditions rated 2 and higher positively affect the end price, indicating that consumers place significant value on better product conditions, the Excellent condition (rating 3) tends to have the greatest impact on increasing the auction price, even more so than

the Certified-Refurbished condition. This observation suggests that consumers perceive the Excellent condition as sufficiently indicative of high quality, perhaps valuing it more for its balance of quality and cost than the premium Certified-Refurbished condition. This nuanced view of consumer perception highlights the importance of condition ratings in influencing auction outcomes and consumer trust in product quality.

7) Historical sales (*HIST_SALE*)

The feature *HIST_SALE*, which tracks historical sales, plays a relatively minor role in the model's predictions as it ranks as the second lowest among the variables. The impact of *HIST_SALE* on the predictions varies depending on its value. Specifically, when *HIST_SALE* is below 96.74, it tends to negatively influence the majority of the predictions, leading to a decrease in the predicted end price. In contrast, as *HIST_SALE* values rise above this threshold, their effect becomes positive, contributing to an increase in the predicted outcome. This dynamic shows that lower *HIST_SALE* values are associated with lower predicted prices, while higher values correlate with higher prices. Notably, when *HIST_SALE* reaches extremely high levels (e.g., greater than 230), it can significantly boost the end price. This observed pattern, as corroborated by research from Liu and Popkowski Leszczyc (2023), Xie, Mao and Wu (2019), and Ye, Cheng and Fang (2013), indicates that higher historical sales figures are a strong positive indicator for the final auction price, suggesting a clear link between a product's sales history and its perceived value at auction.

8) Duration (*DURAT*)

This feature ranks among the lowest in terms of its influence on the auction ending price, suggesting that its overall impact is minimal. However, as the duration (*DURAT*) of the auction

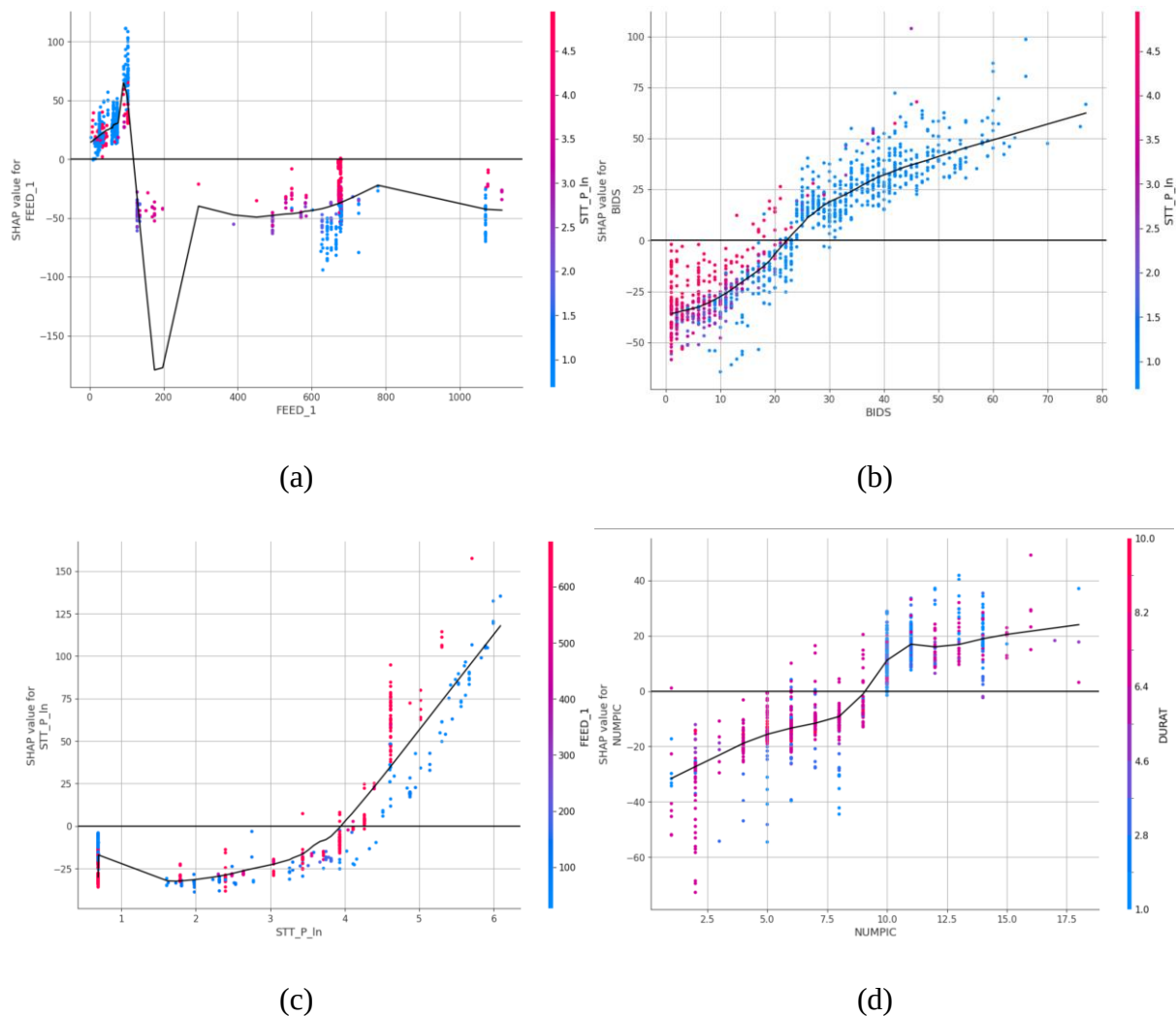
increases, its effect on the final auction price becomes increasingly negative. Notably, this negative impact becomes significant when *DURAT* exceeds a value of 2.79 on the trend line. This outcome is consistent with the findings of Ren and Chen (2020), who demonstrated that while a seller's expected profit might initially be positive, it tends to turn negative once the auction period surpasses a certain critical threshold (T). The negative shift observed at the 2.79 criterion in this study closely mirrors their conclusions, underscoring the importance of carefully managing auction duration to avoid diminishing returns. This result further emphasizes that while longer auctions might seem advantageous by providing more exposure to potential buyers, they can backfire once they exceed an optimal length, leading to reduced final prices and potentially lower profits for the seller.

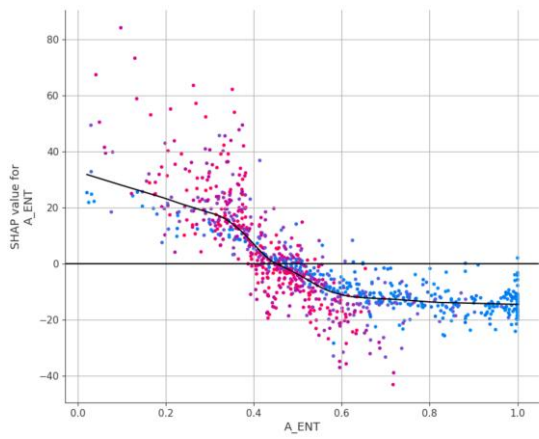
9) Competitive auctions (*COMP_AUC*)

Although *COMP_AUC* ranks low in overall features, it reveals a noteworthy interaction with final auction prices. When the number of concurrent competitive auctions is below approximately 26.36, the variable exerts little to no influence on the predicted final price, with SHAP values remaining close to zero, indicating a neutral effect. However, 26.36 marks a distinct threshold; beyond this point, the feature's impact turns positive, contributing incrementally to higher predicted prices. This shift suggests that high levels of concurrent auction activity may signal strong market demand or create a sense of urgency among bidders, thus enhancing the perceived value of the item. Although *COMP_AUC* may appear marginal in isolated importance rankings, its influence becomes more pronounced when the market reaches a certain saturation point.

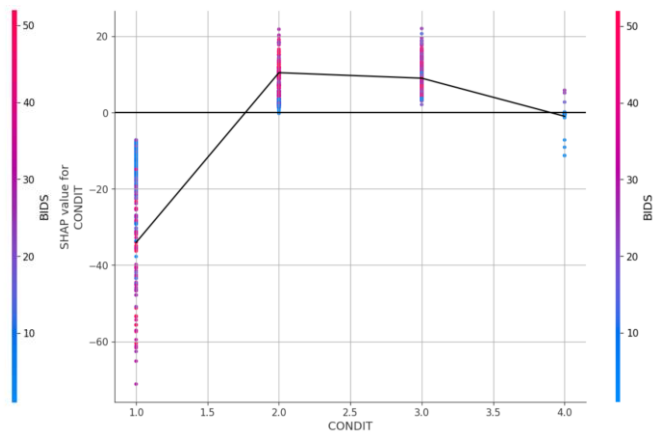
4.4.2.3 SHAP Dependence Plots with Interaction Values

Figure 4.7 provides an initial examination of how individual feature values impact the predicted end price. However, it does not capture the more complex interactions that may exist between variables. To address this limitation, **Figure 4.8** incorporates SHAP interaction values, offering a comprehensive view of how pairs of features jointly affect price predictions. These plots reveal how the combined behaviours of features influence model outputs, going beyond the isolated effects of individual features. By uncovering these interaction patterns, the analysis offers a deeper understanding of the underlying mechanisms that drive auction outcomes, thereby enhancing the interpretability and explanatory power of the model.

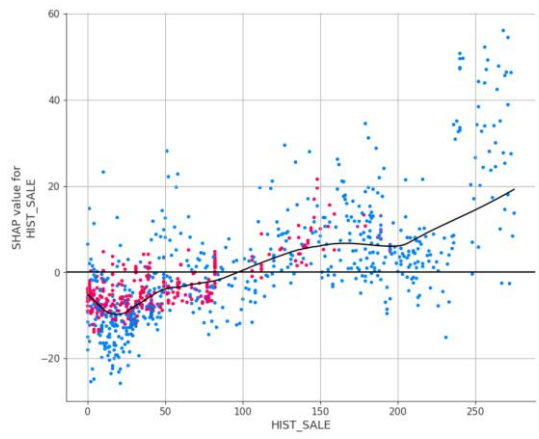




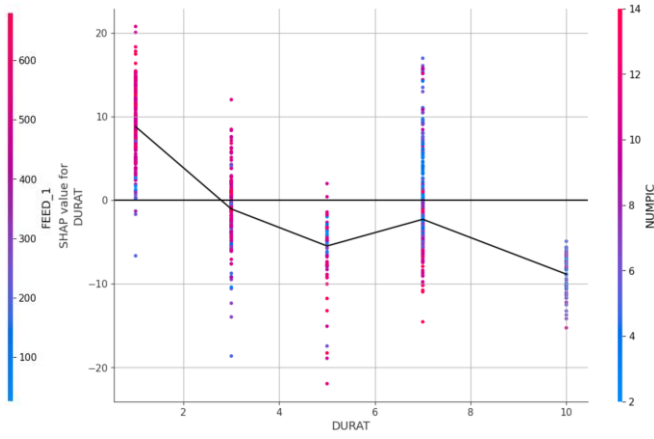
(e)



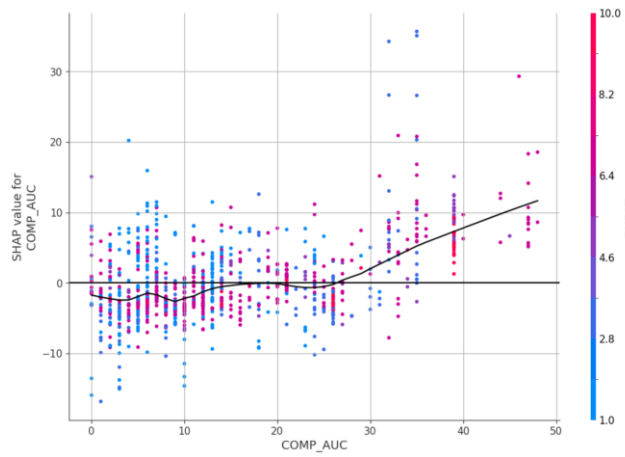
(f)



(g)



(h)



(i)

Figure 4.8: SHAP Dependence Plots with Interaction Effects for Each Feature

- **Feedback Score for the last 1-month (*FEED_1*)**

Figure 4.8(a) illustrates a complex interaction between *FEED_1* and *STT_P_In*, revealing distinct behavioural patterns based on seller experience. As observed in **Figure 4.7**, the distribution of *FEED_1* naturally separates into two sub-groups: sellers with *FEED_1* below 120 and those above 120, each demonstrating notably different auction dynamics.

Among less experienced sellers ($FEED_1 < 120$), *FEED_1* are primarily associated with low *STT_P_In* values. In this segment, a combination of low *STT_P_In* and low *FEED_1* often corresponds to higher final auction prices. The majority of data points in this group cluster around the lowest *STT_P_In*, with limited representation at mid-range and higher levels. This indicates that inexperienced sellers benefit from low entry pricing strategies that reduce buyer hesitation and stimulate competition, as a means to quickly build transaction history and trust.

In contrast, more experienced sellers ($FEED_1 > 120$) exhibit a different pattern. For this group, *FEED_1* appears to have a neutral or even negative marginal effect on final price, consistent with the main effects analysis. Unlike their less experienced counterparts, seasoned sellers are less reliant on low starting prices; instead, they tend to set higher starting prices while still achieving favourable outcomes. This suggests that reputation substitutes for aggressive pricing, enabling experienced sellers to command higher perceived value without needing to trigger bidding activity through low price cues.

Overall, the interaction plot highlights that seller experience moderates the effectiveness of pricing strategies in online auctions. Less experienced sellers gain from low starting prices and

short durations, while experienced sellers leverage their credibility to attract value-conscious bidders without necessarily engaging in price-based competition.

- **Number of Bids (*BIDS*)**

Figure 4.8 (b) examines the interaction between *BIDS* and *STT_P_In* and their combined effects on the final auction price. The key aspect of this plot is how these two factors interplay at different levels of *BIDS* and what happens at the critical point where *BIDS* is 22, which is the point where the trend line crosses the SHAP value of zero, indicating a neutral impact on the predicted price. When *BIDS* is fewer than 22, the effect of *STT_P_In* on the auction outcome varies notably with its value. A higher *STT_P_In* positively influences the end price, suggesting that a higher starting price can enhance the perceived value of the item, thus leading to a higher final price when there are relatively fewer bids. Conversely, a low *STT_P_In* tends to decrease the final price under these conditions, likely because it sets lower initial expectations among bidders regarding the item's value.

Interestingly, when *BIDS* exceeds 22, the dynamics change. At this level, the distinct interaction patterns observed at lower bid counts disappear, indicating that the influence of a high *STT_P_In* becomes very limited. This suggests that beyond this point, the number of bids itself may overshadow the influence of the starting price on the final price outcome. More notably, at the threshold of 22 bids, a high starting price paradoxically tends to lower the final auction price, whereas a lower starting price starts to have a positive effect.

This phenomenon could imply that with a higher number of bids, the competition among bidders can drive the final price independently of the starting price, particularly if the starting

price is perceived as more accessible or attractive. Conversely, a high starting price might deter further bidding beyond a certain point, potentially leading to a lower final price despite a higher initial bid count. This complex interaction offers strategic insights into how sellers might consider adjusting starting prices relative to expected bid counts to optimize final outcomes.

- **Starting Price (*STT_P_In*)**

Figure 4.8 (c) provides a detailed look at how the interaction between *STT_P_In* and *FEED_1* affects auction end prices under different conditions. The plot reveals that at very low *STT_P_In* values, specifically between 0 and 1, an increase in *FEED_1* actually leads to a decrease in the end price rather than boosting it. This suggests that even with higher feedback scores, the very low starting prices may signal lower product value, which isn't overcome by positive feedback.

However, as *STT_P_In* rises above 1, the relationship between *FEED_1* and end price shifts. In this range, a higher *FEED_1* starts to positively impact the end price, contrasting with the effect seen at lower *STT_P_In* levels. This positive influence is visually represented in the plot where red dots (indicating higher *FEED_1*) are positioned above blue dots (indicating lower *FEED_1*), showing that higher *FEED_1* at these levels of *STT_P_In* are beneficial and lead to higher end prices.

Further emphasizing the impact of these variables, the analysis points out that setting *STT_P_In* above 4, especially when combined with a high *FEED_1*, significantly boosts the end price. This finding highlights a potent combination where both a higher starting price and strong seller reputation (as indicated by feedback) work synergistically to maximize auction outcomes. This

intricate understanding allows for strategic adjustments in auction settings to optimize end prices based on the interplay of starting price and seller feedback.

- **Number of Pictures (*NUMPIC*)**

Figure 4.8 (d) explores the interaction between *NUMPIC* and *DURAT*, exploring how these two features collectively influence the auction's end price. The plot identifies *DURAT* as the key feature responsible for the wide vertical spread of SHAP values at fixed *NUMPIC* levels. Specifically, when *NUMPIC* exceeds approximately 8, a shorter *DURAT* is associated with higher SHAP values for *NUMPIC*, indicating a stronger positive impact on the final price. Conversely, when *NUMPIC* is below 8, extended auction durations can help offset the lack of visual detail by building buyer trust over time, leading to higher final prices.

This interaction aligns with the findings of Muthitacharoen and Tams (2017), who observed that short auctions are characterized by high information asymmetry. In longer auctions, bidders have more time to observe and experiment with other participants' bids, thereby gaining additional knowledge and reducing information asymmetry. Similarly, the variables *NUMPIC* and *DURAT* function in a complementary manner within this context. Specifically, when *DURAT* is extended but *NUMPIC* is low, the result is a negative impact on the auction price. Conversely, when *DURAT* is short, but *NUMPIC* exceeds 9.09, the effect on the final auction price becomes positive. This suggests that in short auctions, where information asymmetry is more pronounced, providing more photos can play a critical role in mitigating that asymmetry.

From a business perspective, this suggests that sellers can enhance the perceived value of their items by posting 9-12 photos, particularly during short auction periods. By providing this

optimal range of photos, sellers signal to potential buyers that the item is well-represented, reducing information asymmetry, building buyer confidence and achieving a higher final price.

- **Average Entry Time (A_ENT)**

Figure 4.8 (e) effectively highlights the pivotal role of A_ENT in influencing auction outcomes in conjunction with $BIDS$. It presents a critical observation point, particularly when A_ENT is at 0.45, where the dynamics of the auction change. In scenarios where A_ENT is less than 0.45, which indicates that bidders enter the auction relatively early, there's a noticeable trend where an increase in $BIDS$ tends to drive the end price higher. This suggests that early engagement in the auction, combined with a high number of bids, enhances the competitiveness of the auction, thereby increasing the final price.

Conversely, when A_ENT exceeds 0.45, indicating later participation in the auction, the relationship between $BIDS$ and end price reverses. In this context, higher $BIDS$ result in a lower end price. This could indicate that later entry may lead to a rush of $BIDS$ towards the end of the auction, which might not always increase the perceived value of the item as effectively as early sustained interest does.

Figure 4.8 (e) further illustrates this dynamic with a dense vertical spread of SHAP values between 0.3 and 0.7. This spread indicates strong interaction effects within this range, reinforcing the identified patterns of how timing of entry and bidding activity interact to affect auction prices. The pronounced spread in SHAP values in this interval corroborates the significant influence these variables have on the auction outcomes, particularly highlighting how strategic timing and bid activity are critical in shaping final prices.

- **Condition (*CONDIT*)**

Figure 4.8 (f) offers insights into how *CONDIT* and *BIDS* interact to affect the auction's end price. Notably, when the condition of an item is rated as 1 (Good), the lowest condition, this is typically associated with negative SHAP values indicating a reduction in the end price. This figure also highlights an intriguing dynamic where a lower *BIDS* in this condition category actually results in a higher end price compared to scenarios with a higher *BIDS*. It seems that for items in poor *CONDIT*, fewer *BIDS* do not dilute the perceived value as much as numerous lower *BIDS* might, suggesting that higher *BIDS* could exacerbate the negative perception of an item's poor *CONDIT*.

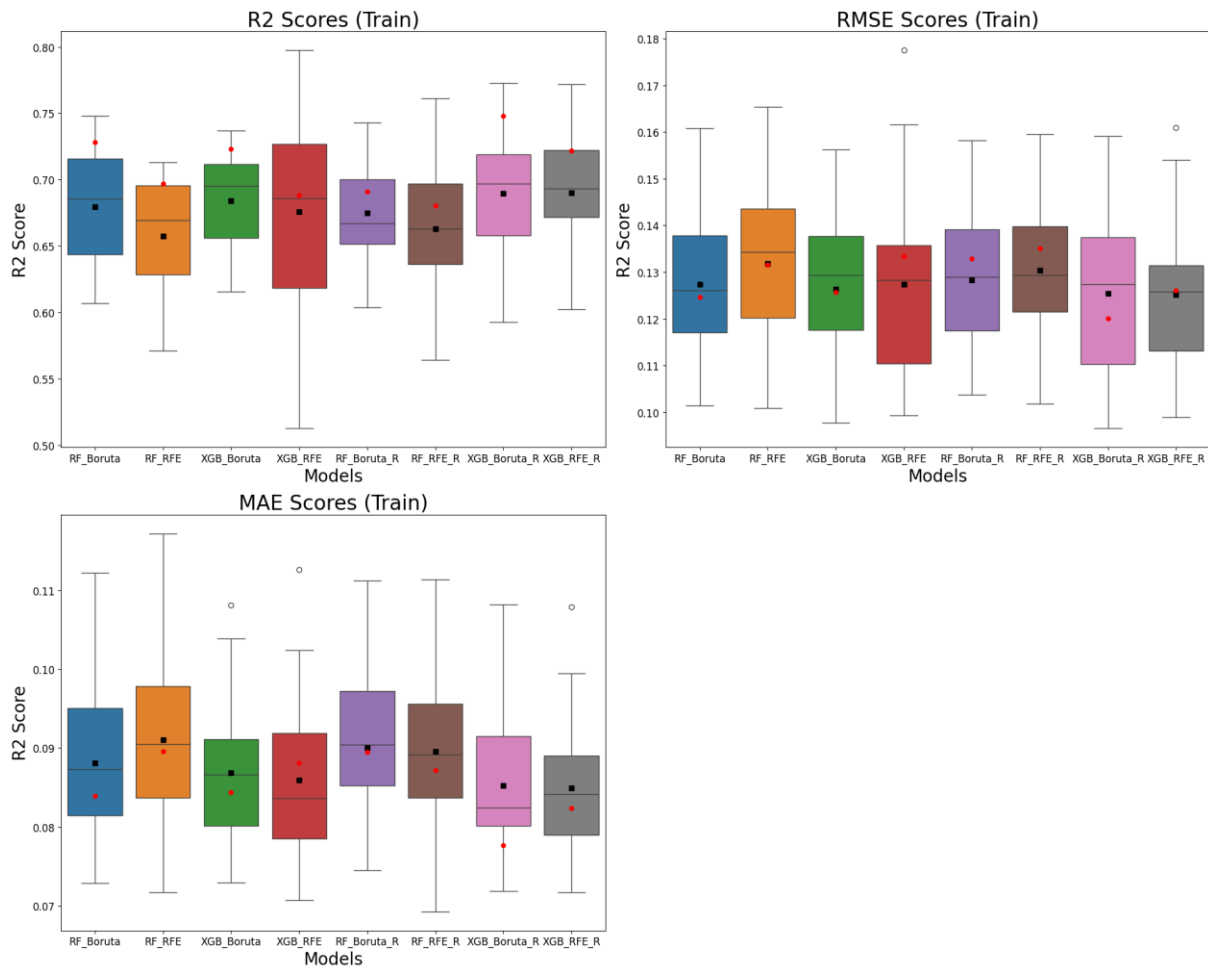
In contrast, for items in better conditions, specifically rated as 2 (Very Good), 3 (Excellent), and 4 (Certified-Refurbished), a higher *BIDS* is shown to consistently increase the end price, as indicated by positive SHAP values. This pattern implies that buyers have greater confidence in the quality of the item based on its higher *CONDIT*, and thus, they are more willing to engage in bidding. This higher engagement, in turn, drives up the final price.

The practical implication here is clear: for products in higher *CONDIT*, encouraging a greater *BIDS* could be a beneficial strategy. This approach can capitalize on buyer confidence and competition to maximize the final auction price. Therefore, sellers might consider strategies such as optimizing listing descriptions or timing auctions to peak periods to attract more bids for items in Very Good to Certified conditions.

4.5 Robustness Check

The study addresses multicollinearity by excluding highly correlated variables, creating suitable conditions to compare LR and ML models effectively. Following this adjustment, the robustness check confirms the superior performance of ML methods and tests whether this performance holds when including all variables, even those initially removed due to multicollinearity.

The findings highlight two key points. First, among all models evaluated during the robustness check, XGBoost combined with Boruta (*XGB_Boruta_R*) achieved the highest performance on both training and test datasets. As shown in **Figure 4.9**, the *XGB_Boruta_R* model outperformed the RF robustness testing model in terms of performance indicators on both the training and testing sets without outliers. This suggests that XGBoost is more effective than the RF model when dealing with a more complex and larger dataset, which in this case includes 16 variables compared to the previous 9. The superior performance of XGBoost can be attributed to its ability to efficiently analyse higher-dimensional data. This advantage of XGBoost over RF in handling complex datasets is supported by various studies (e.g., Bentéjac, Csorgó and Martinez-Munoz, 2021; Gökçe and Duman, 2022).



* ‘_R’ at the end of the title stands for the robustness check dataset)

Figure 4.9: Prediction Results for Robustness Check

First, as illustrated in **Figure 4.10**, the overall results remain consistent with those from the initial models, which addressed multicollinearity, are not significantly different from those obtained in the robustness check models. Although the initial analysis involved removing some features to ensure a fair comparison across various LR models, the inclusion of variables with multicollinearity in the robustness checks did not substantially change the feature importance rankings. Interestingly, variables that were removed due to high multicollinearity in the initial models were later identified as important in the robustness checks. This suggests that even when

all variables, including those with high correlations, are included in ML models, better and more accurate results can still be achieved.

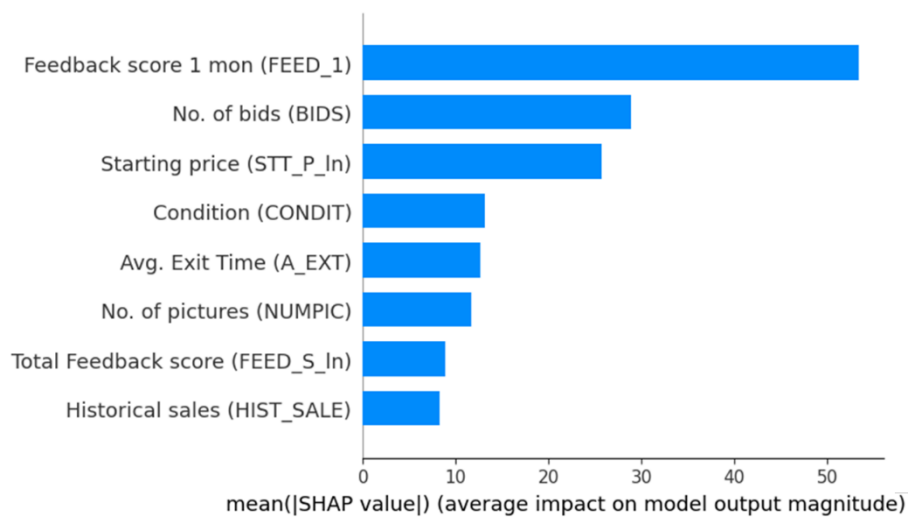


Figure 4.10: SHAP Summary Bar Plot for the Robustness Check Model

In summary, the reintroduction previously removed variables did not significantly affect the variable importance rankings or key metrics like the R2 value as shown in **Figure 4.9**. However, some variables previously removed due to multicollinearity were found to have a high impact on auction prices when reintroduced, while others were excluded by the variable selection algorithm. This underscores the inefficiency of traditional statistical methods that rely on removing multicollinearity. Instead, utilizing ML models that are robust to multicollinearity proves to be more efficient and advantageous. These advanced models not only handle all variables more effectively but also provide a clearer and more comprehensive understanding of the key predictors, highlighting their superiority over conventional statistical approaches.

4.6 Discussion and Managerial Implications

This study has employed predictive ML models alongside SHAP analysis to provide a rigorous examination of the complex dynamics that influence auction outcomes for remanufactured products. The empirical findings demonstrate that ML methods, particularly the *RF_Boruta* model in the initial analysis and the XGBoost model combined with Boruta in the robustness checks, significantly outperform statistical LR models. These methods capture non-linear relationships and intricate feature interactions that are essential in modelling auction prices.

The analysis identified several key variables with a significant impact on final auction prices. Among them, seller feedback score (*FEED_1*), number of bids (*BIDS*), logarithm of starting price (*STT_P_In*), number of images (*NUMPIC*), bidder entry time (*A_ENT*), and product condition (*CONDIT*) emerged as the most influential. Notably, a counterintuitive finding was observed: lower seller feedback scores were associated with higher auction outcomes. Contrary to conventional assumptions, where high feedback scores typically signal trust and command higher prices, this result suggests that less experienced sellers may adopt compensatory strategies, such as setting lower starting prices and using shorter auction durations, to stimulate bidding competition and drive-up final prices.

Critical thresholds were also identified for several key variables, offering concrete guidance for strategy optimisation. For instance, the analysis showed that the number of bids begins to exert a positive influence on the final auction price only after surpassing a threshold of 22 bids. Similarly, the starting price, as represented by *STT_P_In*, demonstrates a significant positive effect only when it exceeds a value of 3.95, which corresponds to approximately £51. Moreover, the number of pictures used in auction listings was found to have an optimal range between 9

and 11 images. Beyond this range, the benefits of additional images appear to plateau, likely due to the onset of information overload, which can detract from rather than enhance buyer confidence. These detailed insights into variable thresholds enable managers to precisely calibrate auction parameters to maximise revenue.

The study further explored the interactions between variables, revealing that the combined effects of certain factors can either amplify or mitigate their individual impacts on auction outcomes. For example, the interaction between *FEED_1* and *STT_P_In* indicates that while less experienced sellers with lower feedback scores tend to benefit from a low starting price, more established sellers can leverage a higher starting price to further boost auction results. Additionally, the interplay between bidder entry time (*A_ENT*) and the number of bids (*BIDS*) is particularly noteworthy. Early bidder participation was found to magnify the positive effect of a high bid count on the final auction price, whereas later entry may diminish this effect. These insights underscore the importance of considering not only the individual contributions of variables but also the synergistic effects that arise from their interactions.

Managerial Implications

This study offers empirically grounded insights with direct managerial relevance, providing actionable recommendations for sellers and platform operators to enhance auction performance in remanufactured product markets:

1) Strategic Calibration of Starting Prices

The findings suggest that starting price strategies should be tailored to seller reputation levels. While low starting prices can boost early bidding activity, they do not guarantee higher final

prices. In contrast, setting starting prices above a certain threshold ($STT_P_ln > 3.95$) positively influences final prices, though it may reduce participation. For lower-reputation sellers, low starting prices may serve as effective signalling tools to attract interest, whereas high-reputation sellers are better positioned to leverage higher starting prices for profit maximisation. Platforms should incorporate these insights into pricing tools or automated recommendations to support novice sellers.

2) Image Strategy Based on Auction Duration

Product images are a critical but context-dependent factor in reducing information asymmetry. The optimal range of 9–11 images yields the most favourable outcomes overall, particularly for auctions of standard duration. However, when auctions are shorter, including more than 10 images helps mitigate the time constraint by offering more comprehensive product visibility, thereby boosting buyer confidence and final prices. Sellers should align image quantity with auction duration, and platforms can enhance user guidance by integrating image-based listing diagnostics.

3) Nuanced Role of Seller Feedback

Although higher seller feedback scores generally correlate with stronger buyer trust, the results show that sellers with lower feedback can still secure high auction prices by leveraging other listing features, such as superior product condition or reduced auction length. This underscores that reputation is not the sole driver of price outcomes, and that strategic compensation is possible. Platforms should offer targeted education and strategy recommendations to help lower-reputation sellers optimise their listings.

4) Leveraging Predictive and Interpretable AI Tools

The demonstrated superiority of ML models, particularly XGBoost and RF in combination with SHAP for interpretability, highlights the value of data-driven auction optimisation. These tools provide granular insight into variable importance and reveal complex interactions among signals. Platform operators should consider investing in predictive analytics infrastructure or partnerships to deliver advanced decision-support tools to sellers, thereby enhancing auction performance and improving platform efficiency through better-informed strategies.

In conclusion, this study provides a thorough investigation into the determinants of auction performance for remanufactured products. By integrating detailed signal analysis with ML models and XAI techniques, it establishes a structured and explainable framework for enhancing auction strategy. Notably, findings such as the non-linear and, at times, inverse relationship between seller feedback and final prices challenge traditional assumptions, offering new perspectives. These insights not only inform platform and seller decision-making but also open avenues for future empirical research on auction dynamics in high-uncertainty markets.

Chapter 5

Differences in the Effects of Market Signals by Remanufactured Product Condition – Evidence from eBay

5.1 Introduction

As highlighted in the Chapter 2, previous research has largely overlooked the distinctions of remanufactured product conditions. Existing studies have predominantly compared either new versus remanufactured products (Guide and Li, 2010; Subramanian and Subramanyam, 2012; Pang *et al.*, 2015; Zhou and Gupta, 2019, 2020) or broader categories such as new, used and remanufactured items (Frota Neto, Bloemhof and Corbett, 2016; Xu, Zeng and He, 2017; McKie *et al.*, 2018; Silva *et al.*, 2018). However, these studies have not adequately explored variations within remanufactured product conditions—an approach comparable to that taken by Kwak, Kim and Thurston (2012) and Makov *et al.* (2019) regarding used products. To fill this research gap, the current study investigates how varying condition levels of remanufactured products influence auction outcomes and critical price determinants.

Since this chapter builds on previous chapters, it maintains a similar overall structure for consistency and coherence. This chapter follows a similar structure to the previous study.

Section 5.2 introduces the dataset used for analysis in this study, detailing the relevant variables and providing descriptive statistics. In Section 5.3, the data preparation process undertaken to establish a robust analytical foundation. Section 5.4 presents the key findings, focusing on the influence of product conditions on auction outcomes. Finally, Section 4.5 offers an interpretation of the results and discusses their managerial implications.

5.2 Data Understanding

Although similar to the dataset employed in Study 1 (Chapter 4), this dataset focuses specifically on distinct condition levels of remanufactured products, facilitating analysis of variations in final auction prices and their determining factors. The dataset encompasses a range of product conditions from Good to Excellent, while Certified Refurbished has been excluded due to its limited sample size. Notably, the variables included in this study are consistent with those in Study 1, ensuring alignment in the analytical framework.

5.2.1 Data Description

This section delivers a clear and thorough overview of the dataset, explaining the selection criteria and organization methods used. By following this systematic approach, researchers ensure that their analyses and conclusions are grounded in a well-defined dataset framework.

- **Data Period and Quantity**

This section provides a comprehensive overview of the dataset used in this study, which builds upon previous research while incorporating a few notable adjustments to better address the research objectives. While the dataset structure and variables are largely consistent with the prior study, 34 products in Certified Refurbished condition have been excluded here due to their

limited sample size. This exclusion ensures that analyses focus on condition categories with sufficient representation, allowing for more meaningful comparisons across different levels of product condition. Through these modifications, this dataset is optimised to provide nuanced insights into condition-based differences in consumer valuation and auction dynamics.

The dataset encompasses transactions of remanufactured electronics sold through eBay auctions from February 15, 2021, to June 29, 2023, offering a range of device conditions rated from Good (1) to Excellent (3). With 1,005 total observations, the dataset includes 323 devices in Excellent condition, 345 in Very Good, and 337 in Good, all sold by certified sellers. This distribution across different condition levels provides a balanced dataset, allowing for a detailed examination of the factors that influence auction prices within the remanufactured electronics market and enabling comparisons based on product quality.

- **Data Format**

The dataset used in this study comprises both structured and unstructured data, building on the approach of the initial study. Structured data includes quantitative elements like final price, starting price, feedback score, and auction duration, which form the dataset's core. Additionally, categorical data, such as product condition, is encoded as ordinal to ensure consistency and enhance analysis accuracy. The dataset also integrates unstructured data, specifically product descriptions, which are non-numeric and converted into numeric form through natural language processing techniques (BERT), as in the previous study, to enable effective analysis. This combined approach deepens the interpretability and richness of the results, as the study leverages both quantitative and qualitative aspects of the data.

5.2.2 Dependent Variable and Explanatory Variables

This study builds on previous work by employing the same dependent and independent variables, thereby creating a consistent analytical framework for comparing various remanufactured product conditions. This methodological continuity enables a more nuanced and comprehensive understanding of the factors driving auction outcomes within the remanufactured market. Beyond merely replicating core variables, the study goes further by examining buyer behaviour and market dynamics, revealing how key variables influence pricing differently across remanufactured product conditions. Consequently, this approach offers deeper insights into condition-specific variations in the remanufactured electronics market, highlighting the unique factors that shape buyer decisions and drive price fluctuations.

5.2.3 Data Exploration

Table 5.1 provides a detailed summary, computing basic statistics for each feature, such as data point count, data type, mean, median and dispersion metrics like variance, standard deviation, and range. These descriptive statistics give a comprehensive overview of the original dataset, identifying trends and variations across variables. Notably, the dataset contains no missing values, with all variables represented numerically as integers or floats.

The dataset comprises 1,005 observations detailing essential attributes of remanufactured electronics sold via auction, revealing critical patterns across metrics. For instance, the End Price (*END_P*) has an average of 210.69 GBP, with prices spanning from 1.20 to 2,850 GBP, indicating a wide range in final auction prices. The Starting Price (*STT_P*) shows significant variation as well, with a mean of 45.68 GBP and a range from 0.01 to 1,231.8 GBP, reflecting diverse initial pricing strategies. The Competitive Auctions metric (*COMP_AUC*) averages

27.07 per listing, indicating moderate auction activity, while Historical Sales (*HIST_SALE*) averages 181.12, offering insight into past sales volumes. The Sentiment Score (*SENTI*), representing the sentiment in product descriptions, has a mean of 0.55, with scores ranging from 0.28 to 0.91, illustrating varied sentiment levels in listings. Listings also feature an average of 8.79 images (*NUMPIC*), with a range from 1 to 19, highlighting differences in visual presentation. Product condition (*CONDIT*) averages at 1.99 on a scale from Good (1) to Excellent (3), showing a mix of conditions. Auction Duration (*DURAT*) averages 4.88 days, ranging from 1 to 10 days, indicating flexible auction lengths. The data also captures competitive dynamics: an average of 24.30 bids (*BIDS*) and 9.9 unique bidders (*BIDR*) per listing suggest strong engagement. Median values of bidders' feedback score (*M_FEED*) vary widely, reflecting different seller reputations, while feedback scores over time (*FEED_S*, *FEED_1*, *FEED_6*, *FEED_12*) show significant fluctuations, indicating shifts in seller feedback across various timeframes.

Table 5.1: Descriptive Statistics for the Original Dataset

Variable	Observations (n=1005)						
	mean	std	min	25%	50%	75%	max
END_P	210.688	193.831	1.200	74.000	185.000	275.000	2850.000
STT_P	45.679	118.483	0.010	0.990	0.990	41.390	1231.800
COMP_AUC	27.065	24.577	0.000	9.000	20.000	37.000	139.000
HIST_SALE	181.122	205.745	0.000	26.000	98.000	254.000	785.000
SENTI	0.551	0.143	0.278	0.445	0.557	0.627	0.914
NUMPIC	8.787	3.481	1.000	6.000	9.000	11.000	19.000
CONDIT	1.986	0.811	1.000	1.000	2.000	3.000	3.000
DURAT	4.877	2.665	1.000	3.000	7.000	7.000	10.000
BIDS	24.303	16.983	1.000	9.000	24.000	38.000	83.000
BIDR	9.897	6.214	1.000	5.000	9.000	14.000	33.000
M_FEED	222.168	689.303	0.000	24.000	89.000	226.000	16884.000
A_ENT	0.598	0.231	0.000	0.429	0.571	0.750	1.000
A_EXT	0.664	0.214	0.000	0.512	0.651	0.829	1.000
FEED_S	42885.087	68524.753	228.000	679.000	18094.000	71939.000	310649.000
FEED_1	267.855	307.606	2.000	64.000	78.000	652.000	1114.000
FEED_6	1745.762	2021.879	19.000	379.000	497.000	4597.000	6897.000
FEED_12	2997.076	3508.387	49.000	471.000	1068.000	7425.000	13103.000

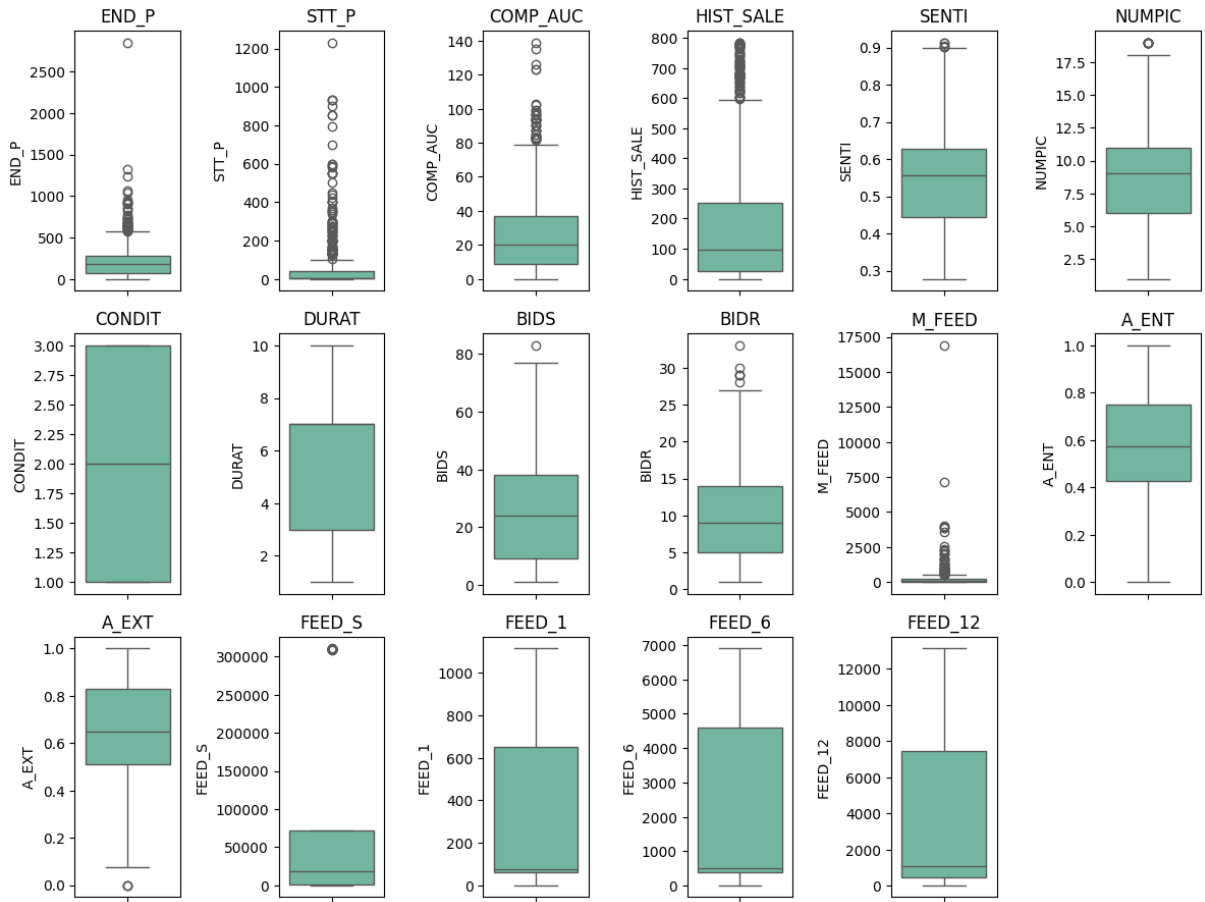


Figure 5.1: Box Plots Showing the Distribution of the Original Dataset

Figure 5.1 presents boxplots demonstrating that variables like *END_P*, *STT_P*, *COMP_AUC*, *HIST_SALE*, *M_FEED*, and *FEED_S* exhibit considerable asymmetry and contain numerous outliers. This step in data exploration is critical for assessing the dataset's readiness for thorough analysis. Properly addressing these irregularities in the subsequent data preparation steps will enhance the dataset's suitability for detailed analysis and more accurate insights.

5.3 Data Preparation

In this study, data preparation follows a methodical approach that focuses on several key stages: data construction, cleaning, selection, and formatting. These steps are vital for guaranteeing the dataset's accuracy and reliability, forming the backbone for valid and meaningful analysis. During each phase, specific challenges, such as handling missing values, identifying and correcting outliers, and addressing any inconsistencies, are carefully managed to prevent distortions in the results. By refining the dataset systematically, this process ensures the information is of high quality and relevant, making it well-prepared for the detailed analysis.

5.3.1 Data Cleansing

In this study, special attention for error was given to feedback scores, where certain entries were marked as “private”, indicating that some users opted not to disclose their scores. As explained in the Study 1, the study employed an imputation method, replacing the “private” entries with the median feedback score to resolve the issue. By imputing with median scores, the feedback variable remained meaningful and comparable across all data points, supporting a robust and valid analysis (Kaiser, 2014). This step was crucial in ensuring the integrity and reliability of the feedback scores in the overall dataset.

The tree-based ML models utilized in this study, such as RF and XGBoost, are naturally robust to outliers, making explicit outlier removal unnecessary (Breiman, 2001; Friedman, 2001). Instead, to optimize data distribution for better analysis, one data point having too high final auction end price is removed, and logarithmic transformations were applied to variables with high skewness, such as *END_P*, *STT_P*, *COMP_AUC*, *HIST_SALE*, *M_FEED* and *FEED_S*. This procedure is explained in the next section.

Additionally, a careful review of the dataset revealed that there are no missing values present. This completeness is essential as it guarantees that the dataset is fully intact and ready for comprehensive analysis. The lack of missing data strengthens the dataset's reliability, simplifying the analytical process and increasing confidence in the accuracy and soundness of the study's results.

5.3.2 Data Construction

As in the previous study, the methodology is divided into two main components: structured data processing and data transformation. Given the use of the same variables as in the prior research, the details of structured and unstructured data transformation steps are not repeated here. Instead, this section focuses on the techniques employed to mitigate skewed distributions.

- **Data Transformation (Log transformation)**

As shown in **Figure 5.1**, several variables in the original dataset contain significant outliers and exhibit notable skewness. Although the ML models used (e.g., RF and XGBoost) are fairly robust to outliers, certain highly skewed variables required transformation to optimize model performance. To address this, logarithmic transformations were applied to variables including *END_P*, *STT_P*, *M_FEED*, *COMP_AUC*, *HIST_SALE*, and *FEED_S*. These transformations effectively compressed the data ranges and normalized the distributions, improving compatibility with ML models. By stabilizing variance and reducing skewness, these transformations enhanced both the reliability and accuracy of the analysis.

5.3.3 Data Selection

In Chapter 4, which compared the performance of LR and ML models, multicollinearity was a concern for LR, prompting the removal of highly correlated variables at this stage. However, the tree-based ML models used in this study, specifically, RF and XGBoost, have natural resistance to multicollinearity, unlike LR, which can be affected by inter-variable relationships. RF and XGBoost evaluate the importance of individual features independently in the feature-splitting process, thus minimizing correlation concerns. This robustness allows these models to handle correlated variables without the redundancy or overfitting risks that might arise in other models. Consequently, no additional preprocessing was needed to manage multicollinearity, which allows all relevant features to remain in the analysis and enhances the reliability of feature importance assessments.

5.3.4 Data Scaling

This process typically addresses differences in units or scales among variables, ensuring the data is ready for accurate comparison and analysis. However, since tree-based ML models like RF and XGBoost are inherently insensitive to the scale of the data, scaling transformations such as MinMaxScaler are not necessary (Breiman, 2001; Friedman, 2001). These models operate effectively without standardization, as they rely on data splits rather than distances or magnitudes. Consequently, all variables contribute appropriately to the analysis without introducing scale-based biases, maintaining model accuracy and performance even without additional scaling steps.

5.4 Empirical Results

In the previous data preparation phase, the dataset was carefully processed to optimise its suitability for analysis. **Table 5.2** presents a comprehensive statistical summary, detailing measures of central tendency, variance, and the transformations applied to each variable. This summary provides a clear view of the auction results and highlights influential factors in price determination. Although the log transformation applied to certain variables has not completely eliminated outliers compared to the original data, it significantly enhances the dataset's alignment with analytical requirements by refining its statistical distribution, thereby improving both interpretability and robustness.

Table 5.2: Descriptive Statistics for the Overall Dataset Used in Analysis

	Observation (n=1004)						
	mean	std	min	25%	50%	75%	max
END_P_In	4.938	1.034	0.788	4.317	5.218	5.620	7.185
STT_P_In	1.948	1.821	0.010	0.688	0.688	3.756	7.117
COMP_AUC_In	2.928	0.988	0.000	2.303	3.045	3.638	4.942
HIST_SALE_In	4.334	1.571	0.000	3.296	4.590	5.541	6.667
SENTI	0.551	0.143	0.278	0.445	0.557	0.627	0.914
NUMPIC	8.787	3.483	1.000	6.000	9.000	11.000	19.000
CONDIT	1.985	0.810	1.000	1.000	2.000	3.000	3.000
DURAT	4.875	2.666	1.000	3.000	7.000	7.000	10.000
BIDS	24.272	16.962	1.000	9.000	24.000	38.000	83.000
BIDR	9.888	6.211	1.000	5.000	9.000	14.000	33.000
M_FEED_In	4.294	1.563	0.000	3.219	4.505	5.426	9.734
A_ENT	0.598	0.231	0.000	0.429	0.571	0.750	1.000
A_EXT	0.664	0.213	0.000	0.513	0.651	0.829	1.000
FEED_S_In	9.143	2.165	5.434	6.522	9.803	11.184	12.646
FEED_1	268.120	307.645	3.000	64.000	84.500	652.000	1114.000
FEED_6	1747.468	2022.163	19.000	379.000	498.000	4597.000	6897.000
FEED_12	2999.924	3508.972	49.000	471.000	1068.000	7425.000	13103.000

Figure 5.2 further illustrates the prepared dataset, covering all remanufactured product conditions (Good, Very Good, and Excellent). The box plots within the figure identify minor outliers among variables, including those subjected to log transformation, and also reflect the

removal of an extreme data point in the *END_P_In* variable. This adjustment not only removes a key outlier but also strengthens the dataset's overall readiness for detailed analysis.

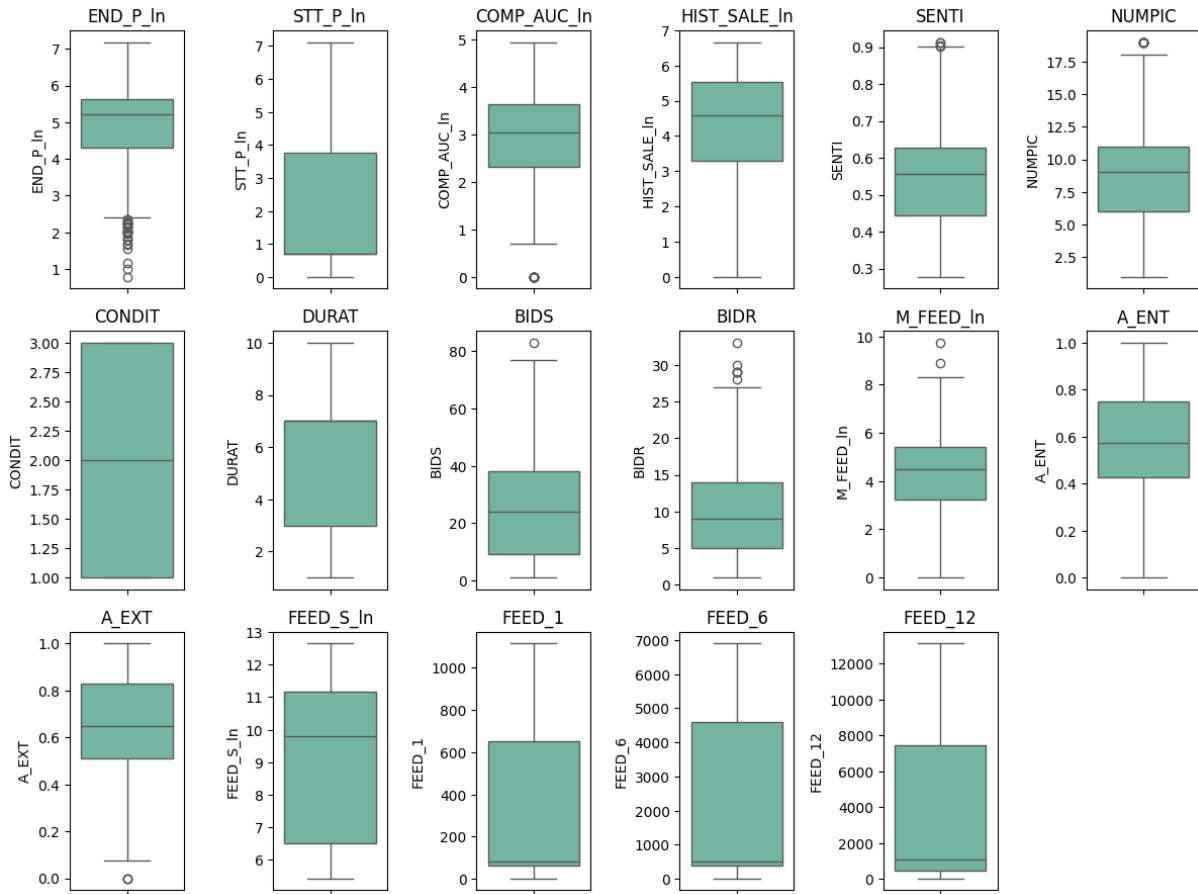


Figure 5.2: Box Plots Showing the Distribution of the Overall Dataset for Analysis

The first analysis in this study involved examining the entire dataset, focusing on identifying the most significant variables affecting price and understanding variable interactions. Since only ML models were employed, as in the Robustness Check method in the previous study, all variables were analysed, including those with multicollinearity and outliers. The dataset was split into an 80:20 ratio for training and testing, allowing the model to learn from a substantial portion of the data while retaining a separate set for unbiased evaluation. As shown in Appendix **Table A.5**, multiple split ratios (80:20, 70:30, and 60:40) were compared, and the 80:20 split

was selected based on cross-validation and test set performance, which demonstrated the most optimal balance between learning capacity and generalisability. To ensure the reliability of results, 10-fold cross-validation was conducted three times to yield averaged scores for consistent comparison, and hyperparameter tuning was applied to maximise model performance. The results across four cases were then evaluated using RFE and the Boruta algorithm for feature selection within two models, RF and XGBoost.

As illustrated in **Figure 5.3**, all prediction values were contained within the statistical range of the training data, indicating a well-trained model. The R^2 scores show that the XGBoost model combined with RFE attained the highest R^2 value in the training set, demonstrating superior predictive accuracy. Across performance metrics, this combination displayed a consistently close alignment between the training data distribution and predictions, outperforming other combinations with lower scores. Ultimately, the XGBoost model with RFE emerged as the most effective approach, achieving an average R^2 of 0.8462 over three repetitions of 10-Fold cross-validation on the training set, signifying robust explanatory power. The test set performance yielded an R^2 of 0.8165, further validating the model's predictive effectiveness.

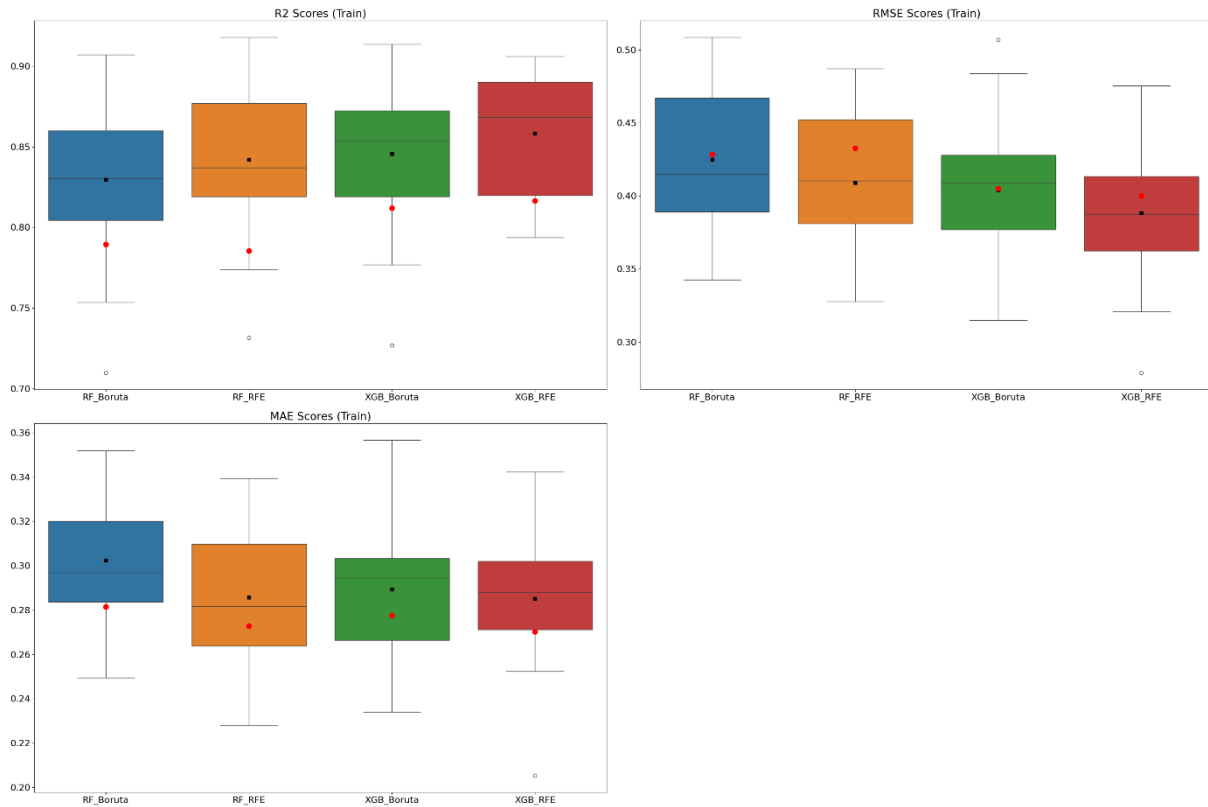


Figure 5.3: Results of Predictive Performances of Models on Training and Testing Sets

Further analysis of variable importance was conducted using the selected model in **Figure 5.3**. **Figure 5.4** presents the ranking of variable importance from the best-performing model. The results show that starting price (log-transformed), number of bids, number of bidders, and feedback score from the past month were among the most important factors. These findings align with the results from Study 1, with the exception of the number of bidders, which was previously excluded due to multicollinearity issues. Product condition also ranked highly, further underscoring its significance in the condition.

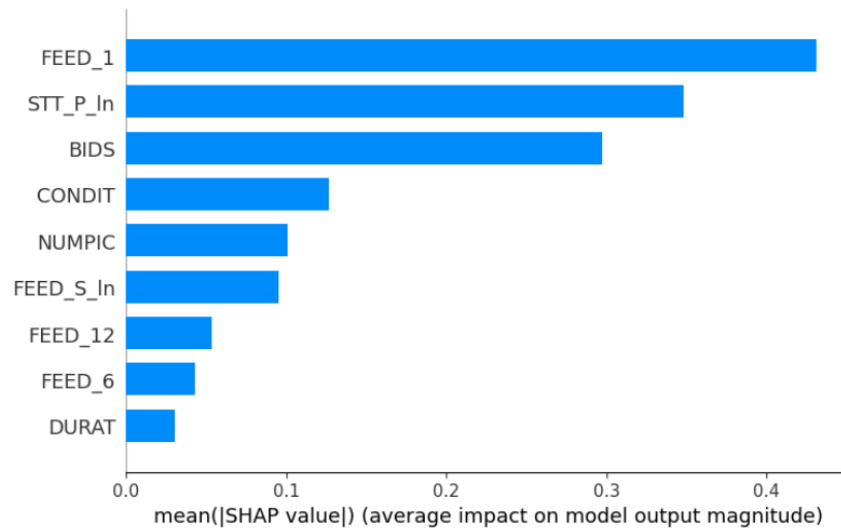


Figure 5.4: SHAP Summary Bar Plot for the Overall Dataset

Figure 5.5 presents a SHAP beeswarm plot, offering a detailed summary of how the top features in the dataset impact the model's output. Each dot on the plot represents a SHAP value for a particular feature instance, with colour indicating the feature value, ranging from low (blue) to high (red). The plot shows how each feature influences the model's predictions across its range of values. The most influential features are positioned at the top of the plot, with *FEED_1*, *STT_P_In*, *BIDS*, and *CONDIT* displaying the highest SHAP values, highlighting their strong impact on the model's output. Specifically, high values of *STT_P_In*, *BIDS*, and *CONDIT* are associated with an increase in predicted outcomes, as indicated by red dots on the right side of the plot. In contrast, lower values of *FEED_1* are linked to higher SHAP values, suggesting that reduced recent feedback positively affects the model's predictions, while higher feedback scores tend to have a negative impact.

This plot also shows *NUMPIC* and *FEED_S_In* as moderately impactful variables, whereas *FEED_12*, *FEED_6*, and *DURAT* have comparatively minor effects on model predictions. The clustering of points around zero for these lower-ranking features suggests minimal influence on

the model's outcomes. Overall, this SHAP beeswarm plot provides a clear view of how each feature, such as feedback scores, bid counts and product condition, affects the model's output, offering a comprehensive understanding of feature importance.

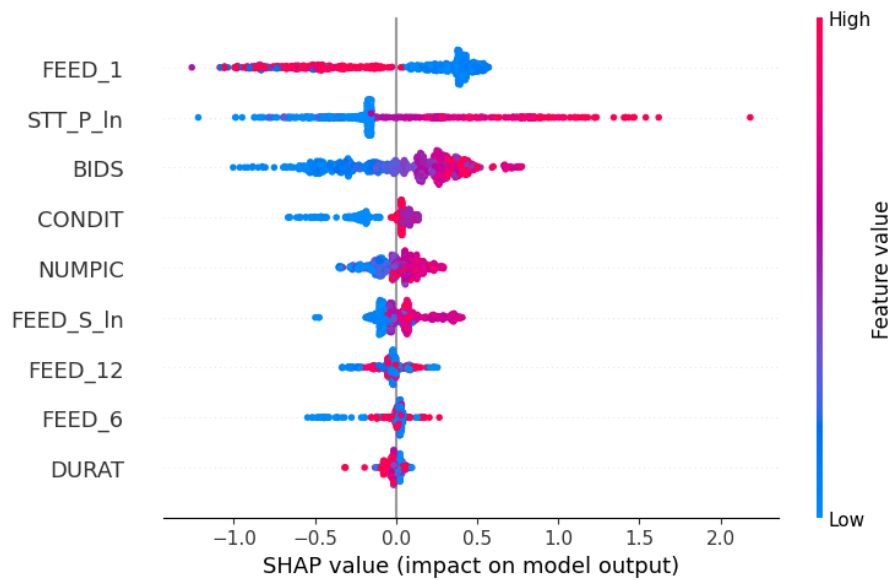


Figure 5.5: SHAP Beeswarm Summary Plot for the Overall Dataset

Up until this point, the methodology closely aligns with previous research. However, a key difference in this study is the division of the dataset into condition-specific subsets, which presents new challenges. As the dataset is split into smaller groups based on product conditions, the reduced sample size within each subset will exhibit different characteristics depending on factors that were less apparent in the full dataset. This systematic approach ensures that the dataset is well-prepared for meaningful insights and robust conclusions.

5.4.1 Empirical Results by Condition

To explore the gap in the literature, specifically regarding the differences in price determination based on product condition, this study further refines the analysis by dividing the dataset into four categories according to the remanufacturing status of the products. This categorization aims to provide a deeper understanding of how different product conditions affect the factors that influence pricing decisions. By segmenting the dataset in this way, the study is able to offer more detailed insights into the role product condition plays in price setting.

First, the dataset was carefully divided into three distinct subsets based on the specific remanufacturing statuses of the products, ensuring that each condition was well-represented. Efforts were made to ensure that the size of each subset is reasonably balanced, minimizing significant disparities in sample size that could skew the analysis. This approach ensures that the results provide a reliable basis for understanding the impact of product condition on price determination. The section below includes descriptive statistics for each subset, allowing for a clearer comparison of how various factors behave across different product conditions.

1) Condition – Excellent

In the Excellent condition subset, several key statistical differences from the Overall dataset (**Table 5.2**) emerge. First, the average of *END_P_In* is significantly higher in the Excellent (5.33) than the Overall (4.94), while *STT_P_In* is notably lower (1.53 vs. 1.95). This suggests a unique dynamic where lower starting prices effectively attract competitive bidding, ultimately driving up final prices for items in excellent condition. The higher average values of *COMP_AUC_In* (3.15 vs. 2.93) and *HIST_SALE_In* (4.88 vs. 4.33) in this subset and suggest

that products in the Excellent subset encounter lower competition and are sold less frequently, likely due to their higher value and more limited market demand.

SENTI is also slightly higher in the Excellent (0.60) than Overall (0.55), hinting at a marginally more positive description from sellers, possibly contributing to the perceived value of these items. Furthermore, products in Excellent condition have a slightly higher average of *NUMPIC* (8.84 vs. 8.79), likely to highlight their quality and appeal visually to prospective buyers. This subset also exhibits greater buyer interest, as reflected in a higher average *BIDS* (29.40 vs. 24.27) and a larger average *BIDR* (11.34 vs. 9.89), suggesting heightened competition for these items. *DURAT* is shorter for the Excellent subset (3.59 vs. 4.87), suggesting that sellers of high-quality items may intentionally opt for shorter auction durations to sustain buyer attention or to create a sense of urgency that drives quicker bids.

M_FEED_In for the Excellent subset (3.93), slightly lower than the Overall dataset (4.29), suggesting that while bidder participation is strong, it may involve many participants with relatively less established experiences. *A_ENT* and *A_EXT* for the Excellent (0.565 and 0.634) are slightly below the Overall average (0.598 and 0.664), indicating earlier bidder entry and earlier exit. This pattern points to more front-loaded bidding activity, possibly driven by focused interest and quicker decisions from less experienced bidders. An interesting trend appears in feedback-related variables, particularly in seller feedback scores. Sellers in the Excellent condition subset have notably lower feedback scores compared to those across the Overall dataset, with *FEED_1* (128.19 vs. 268.12) and other feedback metrics, such as *FEED_6* (783.61 vs. 1747.47) and *FEED_12* (1390.02 vs. 2999.92), being lower as well. This pattern suggests that sellers with lower feedback scores may rely on high-quality product descriptions

and detailed visuals to compensate for their limited reputation. The combination of positive sentiment in descriptions (high *SENTI*) and a greater number of images (higher *NUMPIC*) helps mitigate buyer hesitancy, presenting the product as reliable and of premium quality despite the seller's relative inexperience.

Table 5.3: Descriptive Statistics for the Excellent Subset

	Observation (n=322)						
	mean	std	min	25%	50%	75%	max
END_P_ln	5.3346	0.8676	1.8083	5.0626	5.5215	5.7769	7.1854
STT_P_ln	1.5341	1.7699	0.6881	0.6881	0.6881	0.6881	7.117
COMP_AUC_ln	3.1520	0.9056	0	2.6391	3.2189	3.7377	4.6444
HIST_SALE_ln	4.8797	1.5472	0	3.6889	5.2933	6.2762	6.6670
SENTI	0.6007	0.1289	0.2780	0.5561	0.5643	0.6213	0.9138
NUMPIC	8.8385	2.8403	1	6	10	11	13
DURAT	3.5901	2.6439	1	1	3	7	10
BIDS	29.4016	16.588	1	18	31	41	83
BIDR	11.3416	5.9590	1	7.25	12	15	29
M_FEED_ln	3.9033	1.6291	0	2.6391	3.9316	5.0913	8.2878
A_ENT	0.5654	0.2306	0	0.4	0.5455	0.7143	1
A_EXT	0.6335	0.2127	0	0.4805	0.625	0.7974	1
FEED_S_ln	7.7902	1.9868	5.5722	6.5236	6.5236	10.2760	12.646
FEED_1	128.1925	204.471	3	64	74	94.25	1070
FEED_6	783.6056	1311.818	19	376	434	618.5	6897
FEED_12	1390.016	2540.854	49	456	680	1167.5	13103

- **SHAP Summary Analysis**

The SHAP summary bar plot (**Figure 5.6**) and beeswarm plot (**Figure 5.7**) provide a clear view of the relative importance and directional influence of each predictor on final auction price for remanufactured products in Excellent condition.

Among all features, *SENTI* exerts the strongest impact. Listings with higher *SENTI* values (in red) show consistent upward influence on predicted prices, indicating that emotionally positive or persuasive language significantly enhances perceived product value. Conversely, negative sentiment (in blue) lowers price expectations, confirming the sensitivity of buyers to textual

tone. *STT_P_In* is the next most influential feature. Higher *STT_P_In* values are associated with increased SHAP values, suggesting that elevated starting prices may act as psychological anchors, ultimately contributing to higher final auction prices. This is aligned with Ariely, Loewenstein and Prelec (2003), showing that initial price cues strongly influence buyer valuations. *BIDS* also contributes strongly to auction prices. As *BIDS* increase (in red), SHAP values rise accordingly, reflecting intensified buyer competition. A higher *BIDS* indicates strong buyer interest, which in turn drives the price upwards (Highfill and O'Brien, 2007).

FEED_1 exhibits a complex relationship with predicted prices. Lower values (in blue) are linked to higher price predictions, while higher values (in red) show a slight negative effect. This may indicate that newer or less-established sellers are offering attractive items that draw bidder interest. The effect appears context-dependent, potentially influenced by interactions with factors such as auction duration and item condition. *A_ENT* contributes positively, with earlier bidding activity (higher values in red) linked to higher final prices, possibly due to early engagement indicating strong buyer interest.

FEED_S_In shows a consistent positive impact on final auction prices, unlike *FEED_1* and *FEED_6*, which display negative effects at higher values. This suggests that while recent feedback may reflect short-term seller strategies or specific product listings, potentially leading to negative effects, overall feedback serves as a long-term trust signal that positively contributes to price formation. *NUMPIC* has a smaller but positive impact. Listings with more images (red) tend to predict higher prices, reinforcing the role of visual assurance, though its effect is weaker than *SENTI* or *STT_P_In*. *DURAT* and *FEED_6* have minimal average influence, though the beeswarm plot indicates slight variation in effect depending on interaction with other features.

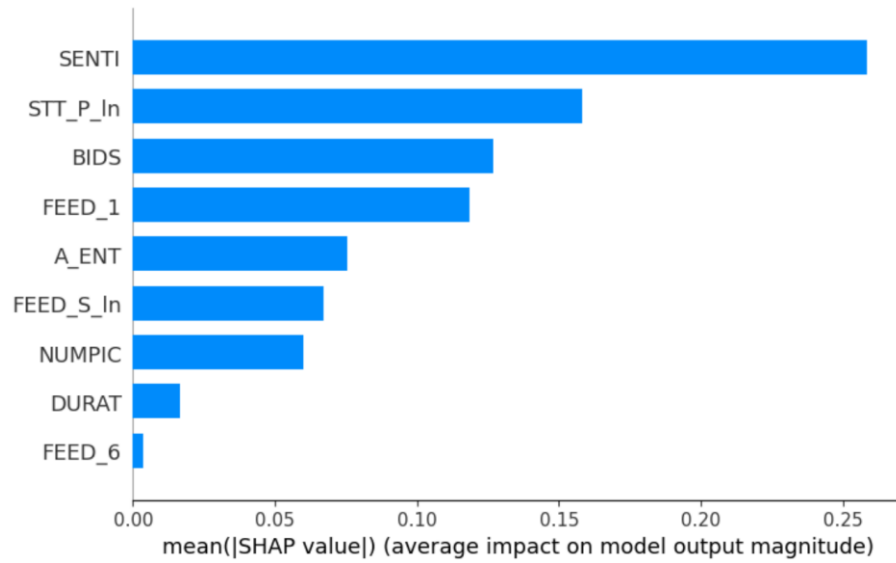


Figure 5.6: SHAP Summary Bar Plot for the Excellent Subset

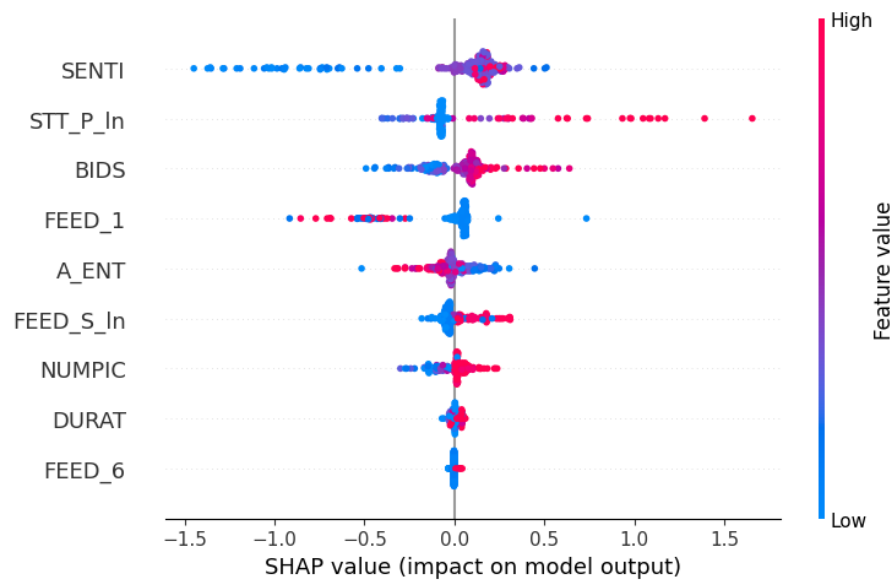


Figure 5.7: SHAP Beeswarm Summary Plot for the Excellent Subset

In summary, *SENTI*, *STT_P_In*, and *BIDS* are the dominant factors driving auction success for Excellent-condition remanufactured products. Feedback signals, particularly recent ones, play a more complex, context-dependent role, while supporting elements such as image count and entry timing help refine price outcomes.

2) Condition – Very Good

The Very Good condition subset (**Table 5.4**) reveals meaningful deviations from the overall dataset (**Table 5.2**), despite the overall average product condition (1.99), nearly identical to the Very Good condition (2). This highlights that, although the subset aligns closely with the average in terms of condition, it exhibits distinct characteristics that set it apart.

The average *END_P_In* for the Very Good subset (5.15) is higher than the Overall (4.94) but lower than the Excellent (5.33), reinforcing the observed trend that better-quality items generally achieve higher final prices. *STT_P_In* for Very Good is 1.48, which is lower than both the dataset of Overall (1.95) and Excellent (1.53). This may reflect a deliberate seller strategy to draw early interest by setting more competitive opening bids for higher-quality products. In terms of competition and sales history, the average *COMP_AUC_In* for the Very Good stands at 2.85, closely aligned with the Overall (2.93) but below the Excellent (3.15). Similarly, the average *HIST_SALE_In* (4.34) is comparable to the Overall (4.33) but lower than that of Excellent (4.87). These figures indicate that Excellent items face more competition and are sold more frequently, which may reflect stronger demand for top-quality products or be partially driven by their shorter auction durations that accelerate turnover.

The *SENTI* for the Very Good subset is 0.58, slightly higher than the Overall (0.55) but lower than the Excellent (0.60). This indicates that sellers tend to use positive language to emphasize quality in Very Good listings, although to a lesser extent than in Excellent listings, potentially affecting buyer perceptions positively. The average *NUMPIC* is slightly lower in the Very Good (8.28) compared to the Overall (8.79) and the Excellent (8.84). This suggests that sellers provide an ample number of images to showcase product quality, though not as extensively as for

Excellent condition items. This suggests that sellers provide an ample number of images to showcase product quality, though not as extensively as for Excellent condition items.

DURAT for the Very Good (4.86) is similar to the Overall (4.87) but longer than the Excellent (3.59). This suggests that auction duration tends to increase as item condition decreases, with shorter durations used to create urgency for higher-quality listings. The Very Good subset shows heightened bidding activity (*BIDS* and *BIDR*), with average values of 28.5 and 11.38, compared to 24.27 and 9.88, respectively, in the Overall. This suggests that Very Good items attract interest, though not to the same level as the Excellent subset (29.40 vs. 11.34), which exhibit the highest competition among bidders.

M_FEED_In in the Very Good subset (4.35) is slightly higher than in the Excellent (3.93) and closely aligned with the Overall (4.29). This implies that Very Good items attract bidders with relatively more established feedback profiles compared to Excellent items. Similarly, *A_ENT* (0.562) and *A_EXT* (0.631) in the Very Good are marginally lower than the Overall (0.598 and 0.664), but very close to those in the Excellent (0.565 and 0.634). This suggests that bidding activity for Very Good items tends to start and end slightly earlier than the overall average, though not as pronounced as in the Excellent group.

Feedback Scores (*FEED_1*: 185.8, *FEED_6*: 1,184.63, *FEED_12*: 2196.29) for the Very Good subset are lower than the averages in the Overall dataset (*FEED_1*: 268.12, *FEED_6*: 1747.47, *FEED_12*: 2999.92). This trend suggests that, similar to the Excellent subset, Very Good condition items do not rely heavily on the seller's total feedback to attract buyers. High-quality

listings appear to reduce the need for a strong feedback history, as the product's condition itself may be sufficient to generate interest.

Table 5.4: Descriptive Statistics for the Very Good Subset

	Observation (n=345)						
	mean	std	min	25%	50%	75%	max
END_P_ln	5.146	0.950	0.789	4.710	5.365	5.740	6.949
STT_P_ln	1.485	1.600	0.01	0.688	0.688	0.688	6.399
COMP_AUC_ln	2.855	1.004	0	2.303	2.944	3.584	4.913
HIST_SALE_ln	4.342	1.472	0	3.296	4.736	5.497	6.664
SENTI	0.580	0.138	0.285	0.477	0.591	0.661	0.904
NUMPIC	8.281	4.075	1	5	8	11	19
DURAT	4.855	2.701	1	3	7	7	10
BIDS	28.536	17.121	1	14	30	41	76
BIDR	11.377	6.571	1	7	12	15	33
M_FEED_ln	4.351	1.528	0	3.367	4.564	5.345	9.734
A_ENT	0.562	0.221	0	0.413	0.519	0.7	1
A_EXT	0.631	0.210	0	0.483	0.6	0.75	1
FEED_S_ln	9.310	2.085	5.438	6.828	9.803	10.740	12.646
FEED_1	185.800	271.071	7	37	74	103	1076
FEED_6	1184.632	1738.786	72	227	437	626	6897
FEED_12	2196.287	3287.514	112	434	682	1174	13103

• SHAP Summary Analysis

Compared to the Excellent subset, the Very Good subset displays a notably different prioritisation of price drivers. (see **Figures 5.8 and 5.9**). While *SENTI* was the most impactful factor in the Excellent, its influence is comparatively lower, ranked near the bottom in both SHAP plots. This indicates that for the Very Good, emotionally expressive language in descriptions plays a secondary role in shaping perceived value, possibly because buyers place greater weight on other indicators (e.g., feedback and bid activity). In contrast, *FEED_1* shifts to the most dominant factor in the Very Good, whereas it held a less prominent role in the Excellent. This shift suggests that buyers rely more heavily on recent seller credibility when the product condition does not inherently guarantee premium quality. This may reflect greater buyer sensitivity to risk when condition is not top-tier, making trust-based signals more decisive.

As in the Excellent subset, *BIDS* increased bidding activity exerts a strong positive influence. Higher *BIDS* are strongly associated with higher predicted final prices, reflecting competitive auction dynamics. Notably, this variable ranks second in both conditions, reinforcing the central role of auction competitiveness across condition tiers. *NUMPIC* also gains relative importance compared to its effect in the Excellent. More images correlate positively with final price, indicating that when product condition is not flawless, visual reassurance becomes more important for mitigating uncertainty. This effect is more pronounced here than in Excellent listings, where inherent product quality may reduce the need for visual validation.

FEED_S_In maintains a moderate but consistent positive effect. Unlike recent feedback, which can show counterintuitive impacts depending on value and condition level, *FEED_S_In* shows stable, additive contributions. This implies that long-term reputation continues to matter, particularly in reassuring buyers when condition is not self-explanatory. Another noteworthy distinction is that *STT_P_In* has a more subdued impact here. While still positive, its role is overshadowed by variables related to social proof and market engagement (feedback and bid count). This suggests that in Very Good listings, price anchoring strategies are less effective unless reinforced by active bidding or reputation signals.

The remaining features, *DURAT*, *SENTI*, and *FEED_12*, contribute smaller but meaningful effects. Longer *DURAT* typically lead to higher predicted prices, possibly due to increased buyer exposure over time. While still slightly positive, *SENTI* plays a minor role as a secondary cue when condition is not pristine. Buyers appear to prioritise visual and social signals over

textual framing at this level. Lastly, *FEED_12* shows that longer-term feedback still plays a role in buyer decision-making, though it is less critical compared to the other feedback metrics.

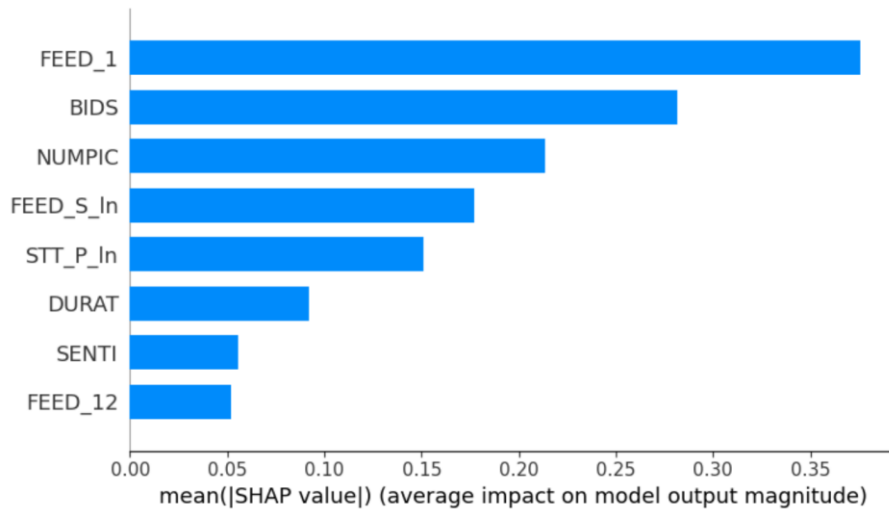


Figure 5.8: SHAP Summary Bar Plot for the Very Good Subset

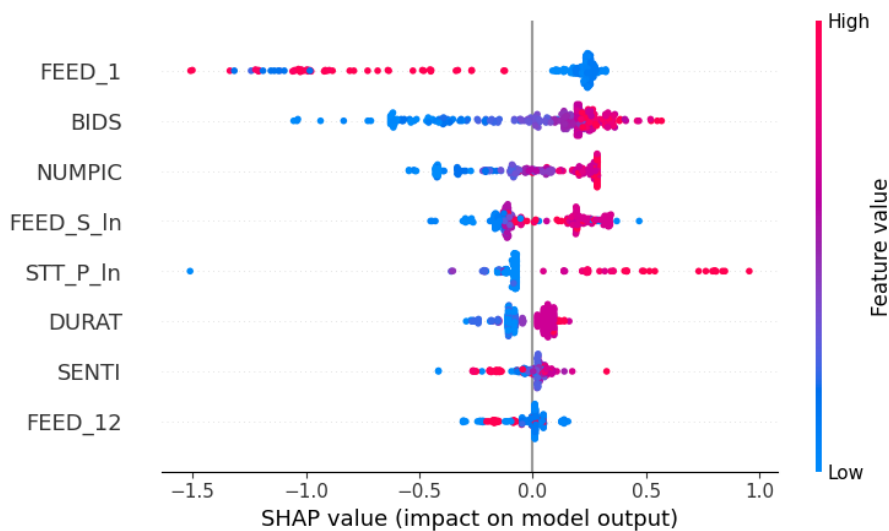


Figure 5.9: SHAP Beeswarm Summary Plot for the Very Good Subset

Overall, in the Excellent subset, *SENTI* and *STT_P_In* ranked highest, reflecting the value of emotional language and price anchoring when product quality was assured. However, in the Very Good subset, the importance shifts toward trust-building (*FEED_1*, *FEED_S_In*) and

visual clarity (*NUMPIC*), indicating that when product condition is not optimal, buyers require more evidence to justify their bids. These findings underscore the need for condition-tailored auction strategies: emotional framing and competitive dynamics for top-tier products, and credibility signals and visual detail for mid-tier items.

3) Condition – Good

The Good condition subset (**Table 5.5**) reveals clear downward deviations across most auction metrics when compared with both the Overall dataset (**Table 5.2**) and higher-quality condition groups (**Tables 5.3** and **5.4**).

The average *END_P_In* for the Good subset (4.34) is lower than the Overall dataset (4.94), which aligns with expectations that lower-quality items fetch lower prices. Interestingly, the *STT_P_In* for the Good (2.82) is higher than the Overall (1.95). This elevated starting price may reflect a strategy by sellers to set a higher starting price to higher starting prices can signal high product quality (Stern and Stafford, 2006; Liang and Chen, 2012; Elmaghraby, Gopal and Pilehvar, 2018) and can lead to higher end prices (Ariely and Simonson, 2003; Stern and Stafford, 2006; Liang and Chen, 2012; Liang, 2014).

Competition and market exposure indicators provide additional insight. The average of *COMP_AUC_In* (2.79) is lower than the Excellent (3.15) and Very Good (2.85) but comparable to the Overall (2.93). *HIST_SALE_In* is lowest in the Good (3.80), reflecting reduced historical transaction volumes, which may be indicative of lower demand or slower turnover for lower-condition products. Descriptive language use also differs. The *SENTI* score in the Good (0.48) is lower than the Overall (0.55), Very Good (0.58), and Excellent (0.60) subset. This points to more neutral or less positive language in product descriptions, possibly reflecting a seller

hesitancy to oversell item quality. On the other hand, *NUMPIC* (average of 9.26) is higher than the Overall (8.79), Very Good (8.28), and Excellent (8.84). This suggests that sellers use a higher number of images to enhance transparency and reduce buyer concerns about item defects.

DURAT is notably longer in the Good, averaging 6.12 days, compared to the Overall (4.87), Very Good (4.86), and Excellent (3.59). This further reflects the inverse relationship between item condition and auction length—lower-quality items require extended exposure to attract sufficient buyer attention. Bidding activity also reflects diminished interest. The Good subset has the lowest averages for *BIDS* and *BIDR* (15.01 and 6.98), compared to the Overall (24.27 and 9.88), Very Good (28.5 and 11.38), and Excellent (29.4 and 11.34). This supports the view that lower-condition products attract fewer bidders and foster less competitive biddings.

Interestingly, feedback metrics trend in the opposite direction. Sellers of Good condition items display the highest feedback scores across all periods: *FEED_1* is 486.09 (vs. 268.12 overall), *FEED_6* is 3,244.63 (vs. 1,747.47), and *FEED_12* is 5,360.89 (vs. 2,999.92). This pattern sharply contrasts with the lower feedback observed in the Excellent and Very Good groups. It implies that sellers with extensive reputations are more likely to deal in lower-condition inventory, relying on accumulated trust to offset perceived product risk.

Table 5.5: Descriptive Statistics for the Good Subset

	Observation (n=336)						
	mean	std	min	25%	50%	75%	Max
END_P_In	4.345	1.001	0.993	3.828	4.394	5.148	6.494
STT_P_In	2.818	1.774	0.688	0.688	3.434	4.394	6.217
COMP_AUC	2.789	1.012	0	2.079	2.833	3.584	4.942
HIST_SALE	3.805	1.516	0	3.091	3.892	5.017	6.661
SENTI	0.475	0.128	0.281	0.368	0.445	0.562	0.901
NUMPIC	9.255	3.320	1	7	9	11	19
DURAT	6.122	1.982	1	5	7	7	10

BIDS	15.006	12.879	1	6	11	21	64
BIDR	6.976	4.923	1	3	6	9	25
M_FEED_In	4.610	1.454	0	3.689	4.727	5.732	8.283
A_ENT	0.668	0.226	0.071	0.500	0.667	0.840	1.000
A_EXT	0.727	0.204	0.143	0.573	0.735	0.905	1.000
FEED_S_In	10.267	1.647	6.075	9.803	11.184	11.184	12.646
FEED_1	486.092	306.564	13	93	673	678	1114
FEED_6	3244.626	2000.859	86	499	4598	4603	6897
FEED_12	5360.890	3284.043	152	1068	7427	7432	13103

- **SHAP Summary Analysis**

As shown in **Figures 5.10** and **11**, in the Good subset, *STT_P_In* emerges as the most influential determinant of final auction price. The SHAP bar and beeswarm plots clearly show that higher starting prices strongly raise predicted prices, indicating that sellers of lower-quality items strategically use price anchoring to convey value—more so than in higher-condition categories, where intrinsic product quality or sentiment may play a stronger role. *BIDS* also exerts a substantial positive effect, albeit within a context of generally lower engagement (fewer bids and bidders) than in the Excellent and Very Good subsets. This suggests that while buyer interest is weaker for Good items overall, the presence of active bidding still significantly boosts auction outcomes. *HIST_SALE_In* contributes moderately, with SHAP values indicating mixed effects depending on context. Unlike in higher-quality subsets, where past transaction volume signals desirability, in the Good subset, it may reflect product saturation or limited novelty, dampening its price-raising effect.

In contrast, seller reputation indicators such as *FEED_S_In* and *FEED_12* show weak or slightly negative impacts. Higher cumulative feedback levels are associated with lower predicted prices, a reversal from patterns seen in higher-condition listings. This may be because experienced sellers disproportionately handle lower-quality goods, leading buyers to discount reputation when condition is poor. Finally, *DURAT* shows a negative relationship with price.

Longer durations are associated with lower SHAP values, suggesting buyers interpret extended listings as a sign of weak demand. This contrasts with Excellent condition items, which perform best under short, urgency-driven auctions.

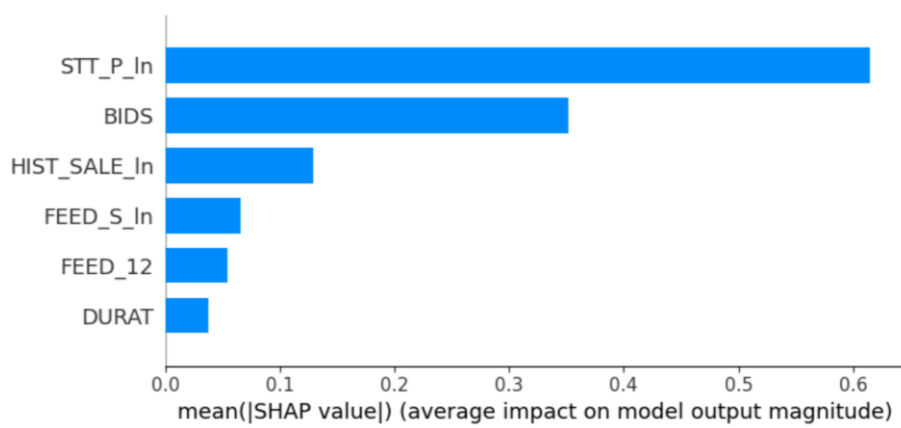


Figure 5.10: SHAP Summary Bar Plot for the Good Subset

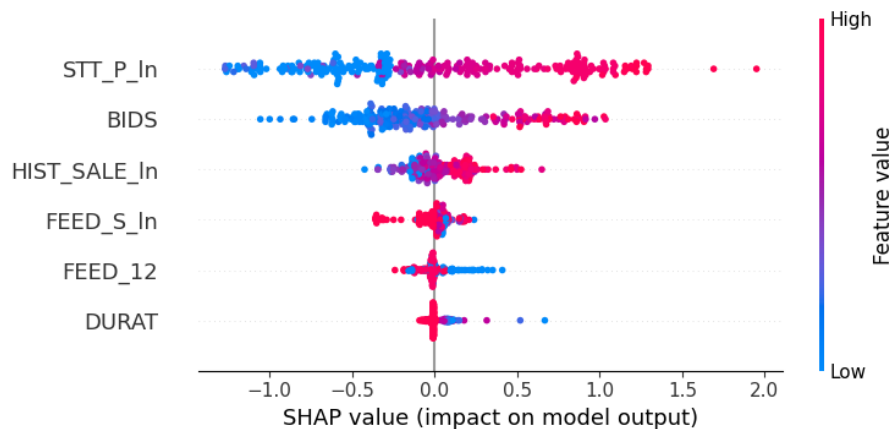


Figure 5.11: SHAP Beeswarm Summary Plot for the Good Subset

Together, these findings indicate that for Good condition remanufactured products, buyers rely more on immediate market cues, such as pricing and active competition, than on seller reputation or long-standing trust signals. This stands in stark contrast to higher-tier items, where affective language, sentiment, and trust-based cues have greater influence.

5.4.2 SHAP Dependence Plot and Interaction Effects

The preceding section presented an analysis of statistical metrics and SHAP values for various features across different remanufactured product conditions, identifying the key factors influencing auction outcomes. Across all conditions, *FEED_1*, *STT_P_In*, and *BIDS* consistently emerged as top predictors for final auction price across all conditions. However, as the quality level of the remanufactured product improves, the importance of *SENTI* and *NUMPIC* becomes more pronounced. This trend suggests that higher-condition items benefit more from positive language and visual appeal, likely enhancing buyer confidence and perceived value. The statistical summaries further reveal distinct seller behaviours and strategies tailored to each product condition, reflecting how sellers optimise their listings to appeal to different buyer expectations based on product quality.

The following analysis explores the key factors influencing auction prices across all remanufactured product conditions, examining their individual impacts and interactions as visualised in SHAP dependence plots. **Figure 5.12** visualises SHAP dependence plots for all variables in the entire dataset, incorporating an additional interaction variable axis. By adding an interaction variable (Variable 2), this approach enables a deeper exploration of the relationship between the target variable and Variable 1, capturing the nuanced marginal effects at fixed values (Molnar, 2025). Additionally, trend lines and marked intersections on the x-axis, where SHAP values equal zero, indicate the points at which these variables start to positively influence final auction prices. This helps identify the thresholds where each factor transitions from neutral to positive effects on price determination.

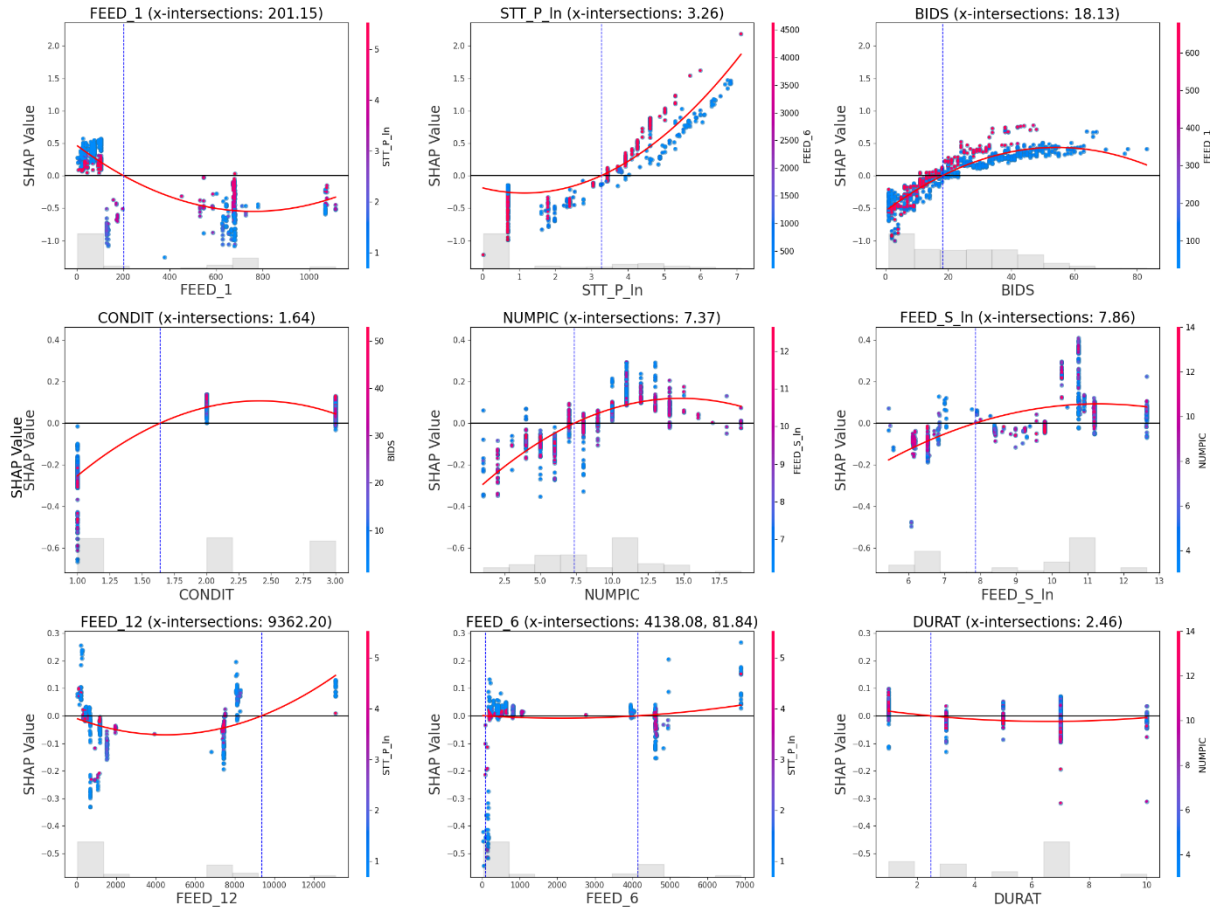


Figure 5.12: SHAP Dependence Plots Showing Interaction Effects (Overall Dataset)

As shown in **Figure 5.12**, *FEED_1* has a complex relationship with final auction prices. Lower *FEED_1* values generally have a positive impact on the final price, while higher values tend to decrease it. Specifically, below a threshold of 201.15, low *FEED_1* values positively influence final prices, but as feedback scores increase, their effect on price turns negative. Interestingly, when interacting with *STT_P_In*, lower *FEED_1* scores with high starting prices negatively impact final prices, whereas higher *FEED_1* scores gradually add value as starting prices rise, suggesting that high feedback may enhance perceived value when paired with higher starting prices. Additionally, the feedback distribution across different product conditions shows that lower *FEED_1* values have a positive impact on higher condition levels, while higher feedback

scores become more advantageous for lower-condition items, indicating that sellers with high experience tend to sell lower-condition products.

Moving from lower to higher *STT_P_ln*, a tipping point around 3.26 (approximately £25) marks where starting price begins to positively impact the final auction price. For sellers with high *FEED_6*, low starting prices negatively affect final prices, whereas high starting prices combined with high *FEED_6* values tend to drive prices up. This pattern suggests that sellers with strong reputations may strategically use higher starting prices to positively influence final auction outcomes. *NOB* has a positive influence on auction prices from around 18.13 bids onward. Within this bid count, high *FEED_1* amplifies the positive effect on final prices. As the number of bids increases, the impact on price continues to rise, though it plateaus around 60 bids, where the rate of price increase begins to slow.

For remanufactured products, lower-condition items tend to have a negative impact on prices (Frota Neto, Bloemhof and Corbett, 2016; McKie *et al.*, 2018), particularly when competing in lower-bid environments. However, from a condition level of 1.64 (between Very Good and Excellent), conditions positively affect prices, with higher bid counts boosting this effect. This suggests that higher-condition products are more likely to attract competitive bids, driving up final prices. *NUMPIC* also plays a role, with a positive impact on final prices (Hou, 2007b), especially when the number of photos exceeds 7.37. When fewer images are used, the overall feedback score has a compensating positive effect on the final price. However, as image count rises, this positive feedback effect weakens, and after 12 photos, additional images may actually start reducing the impact of feedback on final prices.

Among the feedback variables, *FEED_S_In* needs to exceed a value of 7.86 (approximately 2,614 points) to start positively influencing the final auction price. This implies that a strong overall feedback score builds buyer confidence, positively impacting final outcomes. For *FEED_12*, lower starting prices generally coincide with lower *FEED_12* values, showing substantial variability in influence. Interestingly, the interaction between *FEED_12* and starting price indicates that higher feedback scores combined with lower starting prices significantly affect prices, while higher starting prices show minimal impact from *FEED_12*. The positive effect of *FEED_12* begins above a threshold of 9,362 points.

Similar to *FEED_12*, lower *FEED_6* values coupled with low starting prices result in a significant negative impact on final prices, while higher starting prices mitigate this effect. *FEED_6* has a more substantial impact when starting prices are low, suggesting that recent feedback helps counterbalance lower initial prices. The auction duration variable shows a generally negative trend, with durations over 2.46 days starting to negatively influence final prices. Shorter auctions with more images positively impact prices, while longer durations diminish the benefit of additional photos. This pattern suggests that longer listing periods may reduce the perceived urgency, leading to less competitive bidding.

Overall, these insights illustrate the complex interplay of factors that collectively shape the final auction price. Feedback scores, starting price, and number of pictures and bid counts emerge as primary drivers, directly influencing buyers' perception of value and willingness to bid higher. In addition to these main factors, product condition, the number of images, and auction duration provide essential context that can enhance or mitigate the impact of these primary drivers. Higher condition levels not only boost the starting price's influence but also attract more

confident and potentially higher bids, especially in competitive bidding environments. A larger photo count gives prospective buyers more visual assurance about the item's quality, positively affecting bids by reducing uncertainty, especially in shorter-duration auctions where time to assess details is limited. These insights collectively highlight the importance of strategically balancing these elements—feedback, starting price, bid activity, condition, photos, and duration—to optimize auction outcomes. By understanding how these factors reinforce or counterbalance each other, sellers can fine-tune their listings to appeal to buyer psychology and market dynamics, maximizing the potential for higher final prices and successful sales.

Additionally, **Figure 5.13** examines the interaction between the variables highlighted in **Figure 5.12** and the remanufactured product condition. This analysis provides deeper insights into how each factor, such as feedback scores, starting price and bidding activity, affects final auction prices differently across various product conditions (e.g., Good, Very Good, Excellent). By integrating product condition into these interactions, **Figure 5.13** reveals nuanced patterns where the impact of certain variables shifts depending on the item's condition level. This interaction-based analysis not only underscores the relative influence of each variable on price outcomes but also highlights the specific strategies sellers might adopt to optimize prices based on the condition of remanufactured products. By understanding these interactions, sellers can make data-driven adjustments to their listings, aligning factors like starting price, feedback emphasis, and photo count with the condition level to appeal to targeted buyer expectations and maximize auction performance.

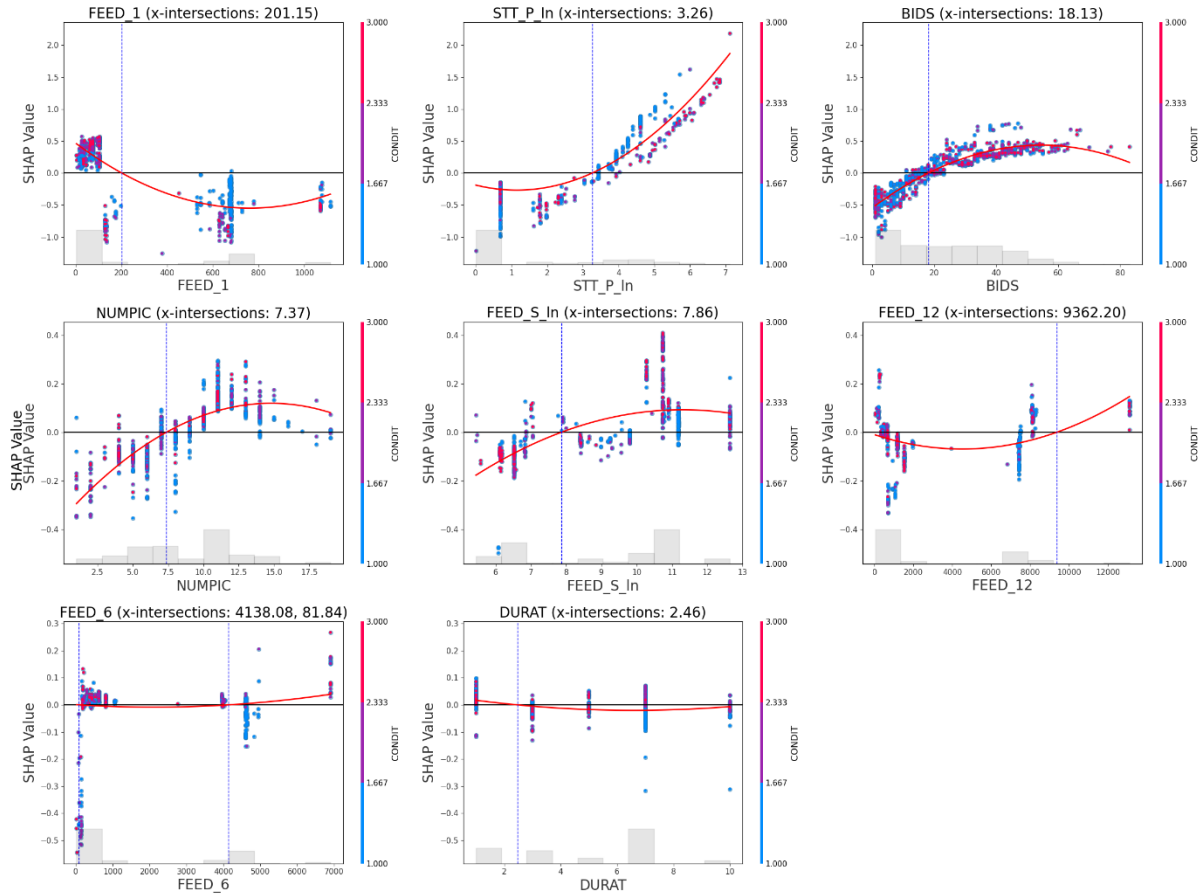


Figure 5.13: SHAP Dependence Plots Showing Interactions Effects with Condition (Overall Dataset)

The relationship between *FEED_1* and auction prices reveals an intriguing pattern. When *FEED_1* scores are below the threshold of 201.15, they positively impact the final price. However, as scores increase beyond this point, the influence turns negative. This effect becomes more pronounced when interacting with *CONDIT*. For instance, lower *FEED_1* scores paired with high-condition products enhance the final price, while higher feedback scores start to lower the price as the condition rating increases. This suggests that high recent feedback scores can reduce final prices, particularly when paired with low-condition items, possibly due to buyers' perceptions of excessive experience with lower-quality products.

Additionally, sellers with low *FEED_1* values tend to positively influence higher-condition items, whereas sellers with high scores find more favourable effects on lower-condition items. This reflects the tendency of more experienced sellers to handle lower-condition items effectively. Starting prices exert a positive effect on auction outcomes once they reach about 3.26 (approximately £25). When looking at the interaction with item condition, lower starting prices positively influence final prices in better conditions. However, as starting prices rise, the condition's effect on price diminishes, indicating that buyers may view high starting prices as setting a value expectation that supersedes condition.

BIDS begins positively impacting auction prices once it reaches around 18.13 bids. For bid counts between 0 and 20, lower-condition items experience a negative effect on final prices. However, as bid counts increase, the positive impact of condition on price also grows, showing that higher bid activity can offset lower condition levels, likely by creating a perception of demand. *NUMPIC* used in listings is another important factor. When a listing includes more than 7.37 pictures, it has a positive effect on final price. In cases where fewer images are used, high condition levels can compensate, adding value to the price. However, as image count continues to rise, the incremental benefit of additional feedback weakens, and beyond 12 images, further photos might reduce the additional positive effect. This aligns with findings from previous analyses, which suggest diminishing returns from excessive visual detail.

A minimum *FEED_S_In* of 7.86 (about 2,614 points) is required for a positive effect on final auction price. Below this threshold, high-condition items have a negative impact on price. Conversely, when total feedback scores exceed this level, higher condition levels contribute positively to the final price, suggesting that consistent, positive feedback helps reassure buyers

about higher-priced items. For *FEED_12*, lower scores combined with high-condition items positively affect the final price, even when *FEED_12* scores are low. When condition is high and *FEED_12* scores are between 8,000 and 12,000, the impact on price becomes increasingly positive, likely due to the accumulated trust associated with long-term seller reputation. High-condition items combined with lower *FEED_6* scores significantly increase final auction prices, whereas high *FEED_6* scores paired with low-condition items tend to decrease prices. *FEED_6* is particularly sensitive to condition at lower feedback scores, suggesting that high-condition items become more appealing when recent feedback scores are modest, as this configuration may convey a sense of rarity or exclusivity. *DURAT* generally has a negative effect on final prices. Beyond 2.46 days, prices begin to drop. However, when auction duration is kept shorter, high-condition items boost final prices. In contrast, durations exceeding 7 days tend to amplify the negative effect of lower-condition items on price, indicating that buyers may perceive extended durations for low-condition items as less desirable or indicative of low demand.

In conclusion, these findings highlight how various factors, such as recent feedback, starting price, bid count, image quantity and auction duration, interact with product condition to shape final auction prices in complex ways. Lower *FEED_1* positively impact high-condition items, while higher scores are more beneficial for lower-condition items, demonstrating how sellers can strategically leverage their reputation to enhance perceived value based on item quality. Similarly, setting an optimal starting price around £25 and maintaining competitive bid activity can significantly elevate final prices, especially for better-condition items.

The diminishing returns seen with additional images and prolonged auction durations reinforce the importance of balanced listing strategies. For instance, while an ample number of photos

can enhance buyer confidence, an excess may lead to diminishing gains, particularly for lower-condition items. Shorter auction durations with high-condition items yield stronger outcomes, while extended durations tend to be less favourable, particularly for lower-quality items.

These insights provide sellers with a comprehensive understanding of how to optimize auction strategies by aligning listing components with product condition. By carefully managing feedback presentation, starting prices, image quantity, and auction duration, sellers can maximize auction outcomes and appeal to buyers' value perceptions effectively.

5.5 Discussion and Managerial Implications

This study provides a detailed analysis of how remanufactured product condition influences price formation in online auctions. By segmenting the dataset into three quality-based subsets—Excellent, Very Good and Good—the findings reveal distinct patterns of buyer response and seller strategy, reflecting varying levels of price sensitivity, signal effectiveness, and reputational reliance across condition tiers.

Excellent Condition

Auctions involving Excellent-condition items achieved the highest final prices (≈ 206 GBP), despite being listed with the lowest starting prices (≈ 3.6 GBP). This strategy appears effective in stimulating early competition, resulting in higher bid volumes and buyer participation. SHAP results show sentiment-laden descriptions (*SENTI*) as the most influential predictor, indicating that emotional framing significantly enhances perceived value at the top quality level. Visual detail (*NUMPIC*) and bid activity (*BIDS*) also contributed positively. Interestingly, sellers with

relatively low feedback scores performed well, likely compensating through strong narrative and visual presentation. Shorter *DURAT* were common, reinforcing urgency and competition.

Very Good Condition

Items in this tier also performed strongly (≈ 171 GBP), though their pricing dynamics shifted from low starting prices (≈ 3.4 GBP). Here, recent feedback (*FEED_1*) became the most decisive variable, overtaking sentiment and visuals. Buyers appear to rely more heavily on seller reputation when product quality is high but not premium. While *SENTI* and *NUMPIC* retained relevance, their marginal effect compared to Excellent items suggests a reweighting of buyer priorities. *DURAT* was slightly longer, and *BIDS* remained high, though slightly below the Excellent subset. Overall, this condition category reflects a balanced reliance on both trust signals and product presentation.

Good Condition

Good-condition items recorded the lowest final prices (≈ 76 GBP) despite having the highest starting prices (≈ 16 GBP). *STT_P_ln* emerged as the most influential factor, with higher starting bids significantly raising final prices, indicating a strong reliance on price anchoring to compensate for limited product quality. *BIDS* also had a positive effect, although overall bidder engagement was lower than in higher conditions. *HIST_SALE_ln* contributed moderately, with SHAP values showing mixed effects depending on context. In contrast, seller reputation metrics (*FEED_S_ln*, *FEED_12*) and auction duration (*DURAT*) exerted weak or negative effects.

Further analysis with SHAP dependence plot with interaction effects for Overall dataset identified several consistent predictors of auction outcomes—starting price, bid activity, sentiment, feedback, and number of images—but their effects vary by condition.

- **Starting Price** acts as a psychological anchor. Prices above £25 begin to positively affect final outcomes, particularly for higher-condition items and sellers with strong feedback.
- **Bid count** drives prices up beyond ~18 bids, with stronger effects for high-condition items. For low-condition products, more bids help offset negative perceptions.
- **Sentiment** becomes increasingly influential at higher condition levels, where positive language significantly boosts buyer valuation.
- **Feedback scores** (*FEED_1*, *FEED_6*, *FEED_S_In*) show a nuanced effect. Low *FEED_1* benefits high-condition items; high feedback scores are more effective for lower-condition ones. *FEED_S_In* above 7.86 ($\approx 2,614$) begins to positively impact prices.
- **Number of Pictures** (*NUMPIC*) enhances perceived value, especially between 7 and 12 images. Beyond this, the benefit tapers off or reverses.
- **Auction Duration** (*DURAT*) over 2.46 days starts to reduce final prices. Shorter auctions are more effective for high-quality items, while longer ones hurt low-condition listings.

Auction outcomes are shaped by how sellers align listing strategies with product condition. High-condition items benefit from early bidder engagement, concise listings, strong visuals, and positive sentiment. Low condition items, in contrast, rely more on seller reputation and competitive bidding to signal trust and drive value. Balancing these elements is essential for maximising auction performance.

Managerial Implications

The findings of this study offer a comprehensive, evidence-based framework for optimising seller strategies in online auctions of remanufactured products. The implications extend across three key domains: pricing strategy, product presentation, and reputation management—each tailored to varying product conditions.

1) Pricing Strategy by Condition Level

For higher-quality items (Excellent and Very Good), adopting lower starting prices is a consistently effective strategy. As shown in the empirical analysis, lower initial bids stimulate early participation, foster competitive dynamics, and ultimately drive up final sale prices. These items tend to attract strong buyer interest, and initiating auctions with a low entry barrier amplifies this effect. SHAP analyses further confirmed that bid volume significantly enhances price outcomes, making starting price a strategic lever. In contrast, lower-condition products (Good) benefit from moderately higher starting prices. While counterintuitive, this approach functions as a quality signal, especially in the absence of intrinsic product excellence. Higher starting prices, when combined with strong seller reputation, can improve perceived value and initiate a more favourable framing effect. However, the SHAP results indicate that this strategy only works effectively when accompanied by active bidding, suggesting that pricing alone cannot compensate for low engagement.

2) Product Presentation and Communication

Across all condition categories, product presentation plays a pivotal role, though its relative impact varies. For high-quality products, emotionally expressive descriptions (as captured by sentiment scores) and rich visual content (e.g., 9–11 images) were key determinants of final

price. These signals help differentiate the listing and reinforce trust, particularly for sellers with limited feedback. For Good-condition items, where product quality may raise concerns, sellers should focus on transparency and clarity. Providing more images, especially those that disclose imperfections, helps reduce buyer uncertainty and supports informed decision-making. In these cases, descriptive content plays a supplementary role, as buyers prioritise objective cues over promotional language.

3) Auction Duration Strategy

Auction duration should also be aligned with product quality. Shorter durations are more effective for Excellent and Very Good products, where urgency can accelerate decision-making and enhance competition. This strategy is especially effective when paired with compelling presentation and pricing. For lower-quality items, however, longer or moderate durations (e.g., 6–7 days) allow for broader exposure and trust-building, particularly when bidding interest is initially weak.

4) Reputation Management and Feedback Positioning

Reputation plays a nuanced role depending on product condition. For Good-condition items, recent feedback (e.g., 1-month and 6-month ratings) is a key asset. Buyers appear to rely on short-term reputation to offset concerns around item quality. Sellers should prominently feature recent positive ratings and consider referencing feedback in product descriptions or profile tags. Interestingly, cumulative feedback (e.g., 12-month or total feedback scores) showed diminishing or even negative effects in the Good category, possibly due to buyer scepticism toward experienced sellers handling lower-quality inventory. This indicates that simply accumulating feedback is insufficient—contextual relevance and recency matter more in

shaping buyer perceptions. For sellers with limited reputational capital, particularly in higher-condition listings, the evidence suggests that strategic use of sentiment-enhanced descriptions and comprehensive visuals can partially compensate for weaker feedback profiles.

In summary, this study underscores the importance of condition-specific strategies in online auctions. By adjusting starting prices, enhancing product presentation, managing auction timing, and aligning reputation signals with product quality, sellers can significantly improve auction performance. These insights not only offer practical guidance for individual sellers but also provide a foundation for auction platforms to develop tools, nudges, or seller support systems aimed at improving efficiency and trust in the secondary product marketplace.

Chapter 6

Unlocking Bidder Heterogeneity in Remanufactured Products Using Explainable Artificial Intelligence

6.1 Introduction

As discussed in **Chapter 2**, prior research has examined bidding behaviours and bidder heterogeneity through a range of analytical methodologies. Building on the foundational work of Bapna *et al.* (2004), subsequent studies have developed and extended bidder taxonomies using varied approaches (Bapna *et al.*, 2004; Shang, Chen and Cheng, 2006; Bapna *et al.*, 2009; Goes, Karuga and Tripathi, 2012; Chang, 2014; Mancha *et al.*, 2014; Lu *et al.*, 2016; Pilehvar, Elmaghraby and Gopal, 2017; Cui *et al.*, 2020). However, these studies have largely focused on general consumer goods and have not explicitly addressed remanufactured products. To fill this gap, the present study investigates bidder heterogeneity in the context of online auctions for remanufactured goods, drawing on actual bidding data from eBay.

This study further advances literature by introducing a hybrid ML framework, referred to as explainable clustering, which jointly captures unobserved heterogeneity and identifies the underlying drivers of cluster formation. By combining unsupervised clustering with supervised classification, the framework transitions from exploratory analysis to explainable model outputs, facilitating a more structured understanding of bidder segmentation. The use of SHAP further

enhances transparency by identifying the key features that influence cluster membership. Moreover, the analysis assesses the relative impact of different bidder segments on final auction prices, offering new insights into how distinct bidding strategies shape auction dynamics. This dual-focus approach not only contributes to the literature of bidder heterogeneity but also provides practical implications for sellers seeking to understand and respond to bidder behaviour in markets for remanufactured products.

Figure 6.1 illustrates the overall research framework, which builds upon seminal end-to-end workflows (Sun *et al.*, 2024b; Alvarez-Garcia *et al.*, 2024; Wang *et al.*, 2024). The methodology proceeds through four systematic steps: (1) Data Collection and Preprocessing; (2) Dimensionality Reduction coupled with Clustering; (3) Classification; and (4) SHAP-based Explanations. This integrated pipeline not only ensures effective segmentation of the dataset but also offers transparent insights into the factors driving the formation of each cluster, ultimately supporting more informed decision-making.

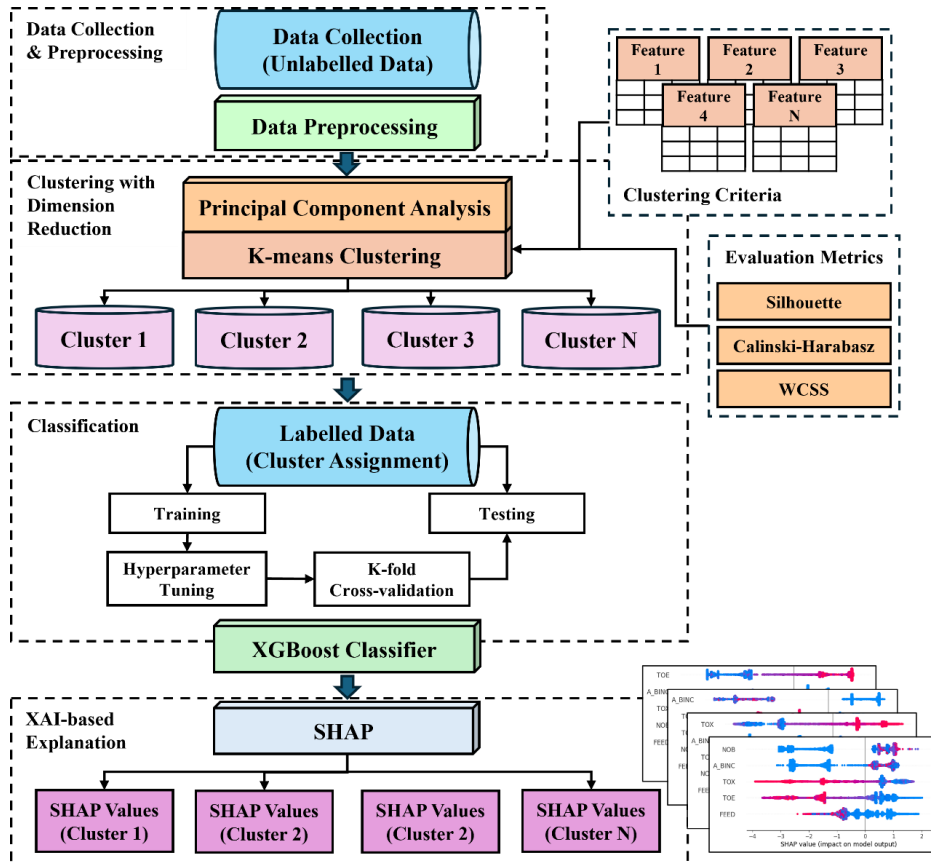


Figure 6.1: Conceptual Research Framework

The chapter is structured as follows. Section 6.2 introduces the dataset and variables. Section 6.3 conducts exploratory data analysis to identify patterns and outliers. Section 6.4 covers data preparation, including handling missing values, normalisation, and PCA. Section 6.5 presents clustering results and bidder typologies. Finally, Section 6.6 discusses key findings, implications, and future research directions.

6.2 Data Understanding

This section provides a detailed explanation of the dataset used in the third study, encompassing the data source, key characteristics, and the criteria applied for clustering. It also outlines the exploratory data analysis procedures conducted to understand the underlying structure and distribution of the data prior to modelling.

6.2.1 Data Description

- **Data Source and Type**

The dataset in this study focuses on bidder behaviour and strategies within remanufactured auctions, specifically examining remanufactured iPhones sold on eBay. This selection is driven by several factors that make the dataset both extensive and representative. Firstly, remanufactured iPhones consistently rank among the best-selling items on eBay, ensuring a broad, robust sample. Secondly, high consumer demand and interest in iPhones result in strong bidder engagement and competitive prices, attracting a diverse pool of bidders with varied motivations. Lastly, the auction listings encompass a wide range of iPhone models, from iPhone 6 to iPhone 12, including model variations like mini, S, Plus, Pro, and Pro Max. This diversity and richness allow for a detailed examination of how specific product features influence bidding behaviour and final auction outcomes.

- **Data Period and Quantity**

The dataset collected from eBay ranges from October 2, 2021, to June 2, 2023. This period was chosen to provide a comprehensive snapshot of the market dynamics for remanufactured iPhones on eBay. It includes 986 transactions and features participation from 13,468 unique bidders, underscoring the wide appeal of the auctions. The study collected detailed information

for each transaction, including not only the final price but also each bid amount and its corresponding bid timing. This bidding history serves as a critical foundation for clustering analysis aimed at exploring bidder heterogeneity.

6.2.2 Clustering Criteria

The selection of appropriate clustering criteria is essential for ensuring both the analytical robustness and interpretive depth of studies examining bidder behaviour in online auctions. Effective criteria should capture multiple dimensions of bidder activity, enabling researchers to uncover nuanced behavioural patterns and differentiate between bidders with varying levels of engagement, strategy, and experience. By incorporating such dimensions, clustering analysis can provide a more comprehensive understanding of auction dynamics and bidder heterogeneity.

This study builds upon established metrics from prior literature, most notably the Number of Bids (*NOB*), Time of Entry (*TOE*), and Time of Exit (*TOX*)—three core variables introduced by Bapna *et al.* (2004) and consistently validated in subsequent research (Bapna *et al.*, 2009; Goes, Karuga and Tripathi, 2012; Chang, 2012, 2014; Mancha *et al.*, 2014; Lu *et al.*, 2016; Cui *et al.*, 2020). These measures have proven effective in distinguishing strategic bidding behaviours and capturing variations in bidder intensity and timing.

To extend the foundational analysis and capture the increasing complexity of online auction environments, this study incorporates additional behavioural indicators such as Average Bid Increment and Feedback Score. These supplementary variables offer deeper insight into bidder aggressiveness and credibility, thereby enriching the assessment of individual bidding strategies. The expanded set of criteria enables a more nuanced classification of bidder types and facilitates

the identification of both conventional and atypical bidding patterns. Together, these measures establish a comprehensive framework for analysing bidder behaviour, supporting the development of detailed bidder profiles and strategic typologies.

1) Number of Bids (*NOB*)

The Number of Bids (*NOB*), also referred to as the Number of Bid Revisions, Bid Frequency, or Frequency of Bidding, is a critical metric that quantifies bidder engagement by measuring the total number of bids submitted during an auction. High-frequency bidding is indicative of a competitive environment and aggressive bidding behaviour, suggesting that bidders are actively contesting the auction, possibly due to lower perceived opportunity costs or higher confidence in their valuation (Bapna *et al.*, 2004). In contrast, low-frequency bidding may reflect a more deliberate and strategic approach, where bidders prioritize careful monitoring and time value, choosing to bid only when necessary (Wilcox, 2000; Bapna *et al.*, 2004). Moreover, *NOB* serves not only as an indicator of participation intensity but also as a proxy for the bidder's time valuation and risk aversion; bidders who face higher costs in terms of time or cognitive load tend to bid less frequently, thereby adopting a more measured strategy (Bapna *et al.*, 2004). This metric thereby provides nuanced insights into both individual bidder behaviour and broader market dynamics, aiding in the differentiation of bidder types and the understanding of auction performance under varying competitive conditions.

2) Feedback Score (*FEED*)

Feedback Scores (*FEED*), derived from the cumulative positive ratings on platforms such as eBay, provide a robust proxy for evaluating a bidder's reputation and historical performance. These scores are widely acknowledged as indicators of reliability, trustworthiness, and market

experience. Empirical evidence consistently shows that bidders with higher feedback scores tend to adopt distinct bidding behaviours. For instance, high-reputation bidders typically submit fewer but more strategically timed bids and are more likely to engage in late-stage bidding, often employing sniping tactics, to optimize their outcomes (Wilcox, 2000; Roth and Ockenfels, 2002; Wang and Hu, 2009) while inexperienced bidder tend to bid more times and overbid (Simonsohn and Ariely, 2008; Livingston, 2010). Notably, many previous studies on bidder heterogeneity have overlooked *FEED* as a clustering feature. By incorporating *FEED* into the segmentation analysis, the research deepens the understanding of competitive behaviour in online auctions, ultimately informing the design of auction mechanisms that can mitigate adverse selection and enhance market efficiency.

3) Average Bid Increment (*ABINC*)

In this study, *ABINC* is defined as the average increment of bids submitted by an individual bidder during an auction—that is, the difference between the highest bid and the lowest bid placed by that bidder divided by *NOB*. This metric differs from traditional definitions, which typically focus on the increment above the previous bid placed by other bidders (Shah *et al.*, 2003; Bapna *et al.*, 2004; Mancha *et al.*, 2014; Cui *et al.*, 2020). Instead, by capturing the full range of a bidder’s activity, *ABINC* provides a more comprehensive indicator of the strategic intensity and aggressiveness of bidding behaviour. A higher *ABINC* suggests that a bidder employs an aggressive strategy, making larger bid jumps that may indicate both a high valuation of the auctioned item and a willingness to incur a “winner’s premium” to outpace competitors.

Conversely, a lower *ABINC* implies a more cautious, incremental approach, potentially reflecting a strategy of careful monitoring and minimal price escalation. When combined with

the Number of Bids (*NOB*), *ABINC* enables a richer classification of bidder types by elucidating the interplay between bidding frequency and bid magnitude. This approach aligns with recent research that advocates for more nuanced measures of bid behaviour. For example, Bapna *et al.* (2004) emphasize the importance of capturing a bidder's overall engagement through multidimensional metrics, while the use of bid range provides additional insight into the variability and strategic decisions underlying each bidder's behaviour.

4) Time of Entry (*TOE*)

Time of Entry (*TOE*) captures the moment a bidder submits their initial bid, marking the beginning of their participation in an auction. This variable is critical in shaping auction dynamics, as it directly influences both participation levels and price formation. Early bids often signal a bidder's commitment and can attract subsequent entrants by enhancing the perceived authenticity of the listing serving as a quality signal (Stern and Stafford, 2006; Elhadary, 2012). Furthermore, early bids can function as sunk costs—psychological investments that commit bidders to the auction, sometimes prompting them to place additional bids if outbid (Ku, Galinsky and Murnighan, 2006).

Conversely, late entry, commonly referred to as sniping, is a strategy where bidders deliberately delay their participation until the final moments of an auction. This tactic minimizes the window for competitors to react and counterbid, effectively reducing the likelihood of triggering a bidding war (Wilcox, 2000; Roth and Ockenfels, 2002; Ockenfels and Roth, 2006). Sniping is often employed by experienced bidders who, by withholding their bids until the auction's closing seconds, can capitalize on the uncertainty inherent in the auction's later stages. This

strategy not only helps in avoiding over-escalation of prices but also enhances the probability of securing the item at a more favourable final price.

In this study, *TOE* is normalized to a 0-to-1 scale, departing from the traditional 1-to-10 scale used in earlier research (Bapna *et al.*, 2004), to ensure consistent comparisons across auctions of varying durations (e.g., 1-, 3-, 5-, 7-, and 10-day events). This normalization enhances the analysis of how entry timing correlates with aggressiveness, risk preferences, and overall auction success.

5) Time of Exit (*TOX*)

Time of Exit (*TOX*) delineates the moment when a bidder submits their final bid, effectively marking the conclusion of their participation in an auction. This metric is instrumental in revealing bidder persistence and the strategic considerations underlying their decision to withdraw. By normalizing *TOX* on a 0-to-1 scale, consistent with the normalization applied to *TOE*, comparability across auctions of varying durations is achieved, thereby enhancing the analytical robustness. The joint examination of *TOE* and *TOX* provides a complex, multi-dimensional perspective on bidding strategies. In certain auction formats, early bids secure time priority, whereas in platforms like eBay, experienced bidders often resort to sniping, delaying their final bid until the auction's closing moments to avoid competitive counterbidding (Wilcox, 2000; Roth and Ockenfels, 2002; Ockenfels and Roth, 2006).

Furthermore, integrating *NOB* into this dual approach deepens the understanding of how the temporal distribution of bidding activity impacts final auction prices and market dynamics. Specifically, it allows us to distinguish between strategies, such as those in which bidders place

an initial early bid to secure time priority and subsequently snipe at the auction’s closing stages to compete at the margin (often termed the sip-and-dipper strategy), and strategies characterized by continuous, multi-stage bidding from early to late phases of the auction.

6.2.3 Data Exploration

Table 6.1 and **Figure 6.2** provide a comprehensive statistical description and visualization of the original dataset. Together, these provide a snapshot of the typical bidding landscape, with notable outliers in both activity and pricing. **Table 6.1** provides a summary of key descriptive statistics based on 13,468 observations. This detailed summary allows for a clear understanding of the distribution and variability of the data, offering insights into central tendencies and the range of each variable.

Table 6.1: Descriptive Statistics for the Original Dataset

Criteria	Observation (<i>n</i> = 13,468)						
	mean	std	min	25%	50%	75%	max
NOB	2.5643	2.8716	1	1	1	3	86
FEED	218.1401	522.5337	-1	1	27	194	23286
ABINC	4.7434	9.8445	0.00000	0.00000	0.00000	5.75694	195
TOE	0.4306	0.3767	0.00057	0.07449	0.29030	0.83923	1
TOX	0.4874	0.3853	0.00075	0.09925	0.41807	0.93275	1

NOB has a mean of 2.56 with a standard deviation of 2.87, indicating that while most listings received only a few bids (25th and 50th percentiles at 1), some attracted significantly more attention, with a maximum of 86 bids. *FEED* shows a wide range, with an average of 218.14 and a high standard deviation of 522.53, reflecting substantial heterogeneity in seller reputation. Notably, the minimum value of -1 suggests the presence of anomalies or data quality issues, while the distribution is heavily right-skewed due to a maximum value exceeding 23,000.

ABINC also exhibits high variability, with a mean of 4.74 and a standard deviation of 9.84. However, the 25th and 50th percentiles are both zero, indicating that in many auctions, no incremental bidding occurred, possibly due to single-bid scenarios or static pricing. *TOE* and *TOX* variables are both normalised between 0 and 1, representing relative timing within the auction. The median *TOE* of 0.29 and *TOX* of 0.42 suggest that, on average, bidders entered relatively early and exited later, though considerable variation is evident across cases. These statistics collectively highlight the diversity in bidding dynamics and seller characteristics within the dataset.

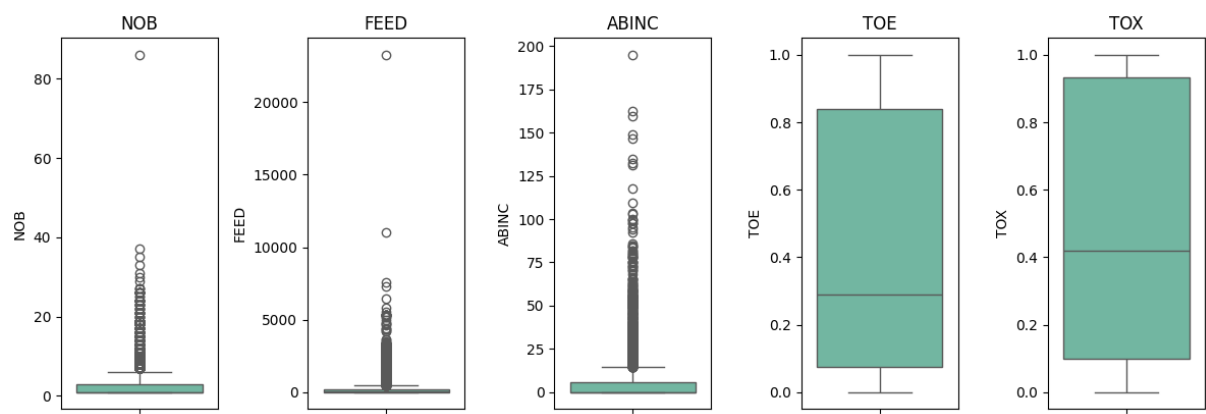


Figure 6.2: Box Plots Showing the Distribution of the Original Dataset

Moreover, **Figure 6.2** presents box plots of the original dataset, showcasing six criteria. As indicated in the table, the criteria in the original dataset, except for *TOE* and *TOX*, exhibit numerous outliers. This visualization helps identify the spread and potential anomalies within the data, providing a visual representation of the variability and skewness of each criterion.

6.3 Data Preparation

Data preparation involves three main steps: data cleaning to remove errors and missing values, data construction to generate meaningful variables, and data scaling to standardise feature ranges for effective analysis.

6.3.1 Data Cleaning

In the dataset, 16 observations for the *FEED* variable were labelled “private”, indicating that these values were obscured by bidders. To address this, a single imputation method was employed, substituting the missing values with the median feedback score. The median value was selected over the mean because of the data’s skewed distribution, thereby providing a more robust central tendency measure. Given that these missing values constitute less than 2% of the dataset (16 out of 13,468 observations), any potential downward bias in variance and correlation estimates is considered negligible (Schafer, 1999; Sainani, 2015).

6.3.2 Data Construction

This section explains the rationale for deriving additional features from existing variables to improve model interpretability and predictive accuracy. By transforming or combining raw attributes, feature engineering helps reveal latent patterns and behavioural signals that are not immediately evident, thereby strengthening the model’s ability to capture complex auction dynamics (Chapman *et al.*, 2000).

1) Derived attribute – Average Bid Increment (*ABINC*)

To capture bidder behaviour with greater granularity, this study introduces a derived variable: Average Bid Increment (*ABINC*). The bid increment (*BINC*), defined as the difference between

a bidder's highest and lowest bids, offers a basic measure of valuation range but fails to account for how that value is built over successive bids. *ABINC* refines this concept by dividing *BINC* by the total number of bids (*NOB*), resulting in an average bid step size. This metric provides insight into bidding style: a high *ABINC* reflects a bold strategy with fewer, larger bid increases, while a low *ABINC* suggests a more cautious, incremental approach with frequent small increases.

When applied as a feature in clustering analysis, *ABINC* yielded more distinct clusters than *BINC* alone, indicating its stronger discriminatory power in profiling bidding strategies. Used in tandem with *NOB*, *ABINC* enables more nuanced segmentation, such as differentiating between bidders who make one or two high-value bids and those who participate through continuous low-increment activity. This enhanced bidder classification contributes to a deeper understanding of auction behaviour and supports the development of more robust models.

2) Data Transformation

From this section, specific techniques for data transformation will be explored in detail. The dataset in **Table 6.1** shows significant skewness and contains numerous outliers beyond three standard deviations from the mean, which can hinder the effectiveness of statistical analyses and ML models. To address this, the Box-Cox Transformation is applied to address the existing issues with outliers and skewed distributions, ultimately preparing the dataset for effective clustering analysis. By implementing these techniques, the dataset will be better aligned with the requirements of K-means clustering, leading to more accurate and meaningful results.

The **Box-Cox Transformation** is a versatile technique for converting non-normal data into a normal distribution, an essential step for statistical methods and ML algorithms that require normally distributed data. It helps to stabilise variance and reduce skewness and outliers. Unlike fixed transformations, such as log or square root transformations, the Box-Cox method optimises the λ parameter using maximum likelihood estimation, allowing it to adapt effectively to a range of data distributions (Box and Cox, 1964; Osborne, 2010).

Table 6.2 provides a detailed statistical summary of the dataset after applying the Box-Cox Transformation, along with the lambda values calculated for each feature. This transformation was applied to address issues of skewness and non-normal distribution within the data, resulting in a more normalised distribution across key variables. As shown in **Figure 6.3**, the transformation notably improves the data's distribution, supporting the assumptions required for various statistical and ML models. Importantly, the features *TOE* and *TOX*, which did not display significant skewness issues, were exempted from transformation and therefore have lambda values set to 0. This selective transformation ensures that only skewed variables were adjusted, preserving the integrity of naturally distributed features and resulting in a more robust dataset for subsequent analysis.

Table 6.2: Descriptive Statistics after Box-Cox Transformation

Criteria	Observation (<i>n</i> = 13,468)							
	Lambda	Mean	Std	Min	25%	50%	75%	Max
NOB	-0.8319	0.3627	0.3854	0.0000	0.0000	0.0000	0.7201	1.1725
FEED	-0.0655	2.9578	1.7364	0.0000	1.0600	3.0216	4.4620	7.3645
ABINC	-0.4925	0.5966	0.6424	0.0000	0.0000	0.0000	1.2380	1.8794
TOE	0	0.5372	0.7169	0.0000	0.0000	0.0000	1.3564	1.7884
TOX	0	0.4305	0.3767	0.0006	0.0745	0.2903	0.8392	1.0000

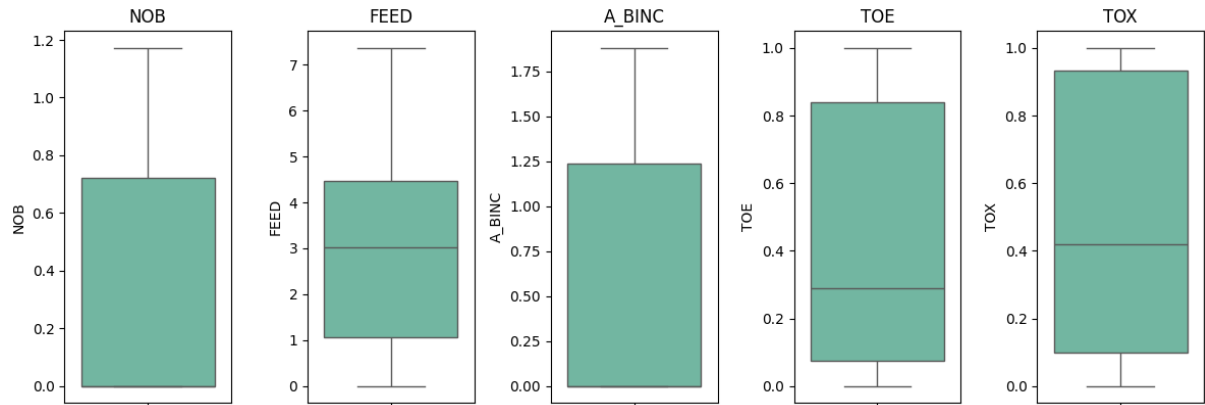


Figure 6.3: Box Plots Showing the Original Data Distribution after Box-Cox Transformation

6.3.3 Data Scaling

Data scaling is a critical preprocessing step for clustering models, such as K-means, particularly those that rely on distance-based computations. Without proper scaling, features with larger numerical ranges can disproportionately influence the outcome, leading to biased clustering results. To address this, the study employs *StandardScaler*, a standardisation technique that transforms each feature by subtracting the mean and dividing by the standard deviation. This process results in a dataset where all features have a mean of zero and a standard deviation of one, ensuring that they are on a comparable scale. This approach is particularly useful when working with features that differ in magnitude or distribution. By applying standardisation, the study ensures that no single feature dominates the clustering process, thereby improving the accuracy and interpretability of the resulting clusters. It also enhances model stability and consistency across different analytical stages.

6.4 Empirical Results and Discussions

This study employs an integrated explainable clustering approach, combining K-means clustering with XGBoost classification and SHAP, to analyse bidder behaviour in online auctions. K-means, a partition-based unsupervised learning method, was selected for its conceptual simplicity, computational efficiency, and scalability across large datasets.

DBSCAN, a widely used density-base model, was simultaneously compared as an alternative. Its performance was assessed by systemically adjusting key hyperparameters: *eps* (neighbourhood radius) and *min_samples* (minimum number of points to form a dense region). Despite this, the best Silhouette score achieved by DBSCAN was approximately 0.4313, substantially lower than that obtained with K-means, indicating inferior cluster cohesion and separation (shown in **Table A.4**). This result confirmed that DBSCAN was unsuitable for the data structure and reinforced the selection of K-means as the preferred clustering method.

K-means was employed to identify natural groupings within the dataset based on similarities in bidder features. These unsupervised clusters were subsequently interpreted using XGBoost, a gradient boosting-based supervised learning algorithm, which classified cluster membership and quantified the contribution of each feature using SHAP values. This combined approach offers both structural discovery and interpretability: K-means exposes the latent grouping patterns, while XGBoost and SHAP reveal the key drivers behind cluster differentiation. Together, these methods yield robust, explainable insights into bidder typologies and enable more informed, data-driven decision-making.

6.4.1 Principal Component Analysis (PCA) results

To investigate the fundamental structure of the dataset and reduce dimensionality, PCA was applied. Beyond its role in visualising high-dimensional data by reducing dimensions, PCA was used to address multicollinearity by transforming highly correlated variables into a smaller set of uncorrelated principal components. As shown in **Table 6.3**, the correlation matrix reveals substantial inter-feature correlations, reinforcing the need to reduce redundancy. By retaining the most informative variance while discarding noise, PCA simplifies the data structure and enhances the efficiency and accuracy of subsequent clustering.

Table 6.3: Correlation Matrix of Clustering Criteria

	NOB	FEED	TOE	TOX	ABINC
FEED	-0.147287				
TOE	-0.161229	0.157103			
TOX	0.015475	0.144226	0.911083		
ABINC	0.900314	-0.105963	-0.108089	0.093176	

The results are summarised in **Figure 6.4**, which displays two key diagnostic plots: the Cumulative Explained Variance (left) and the Scree Plot of Eigenvalues (right). These visualisations aid in identifying the optimal number of components to retain by highlighting both the proportion of variance explained and the relative importance of each component.

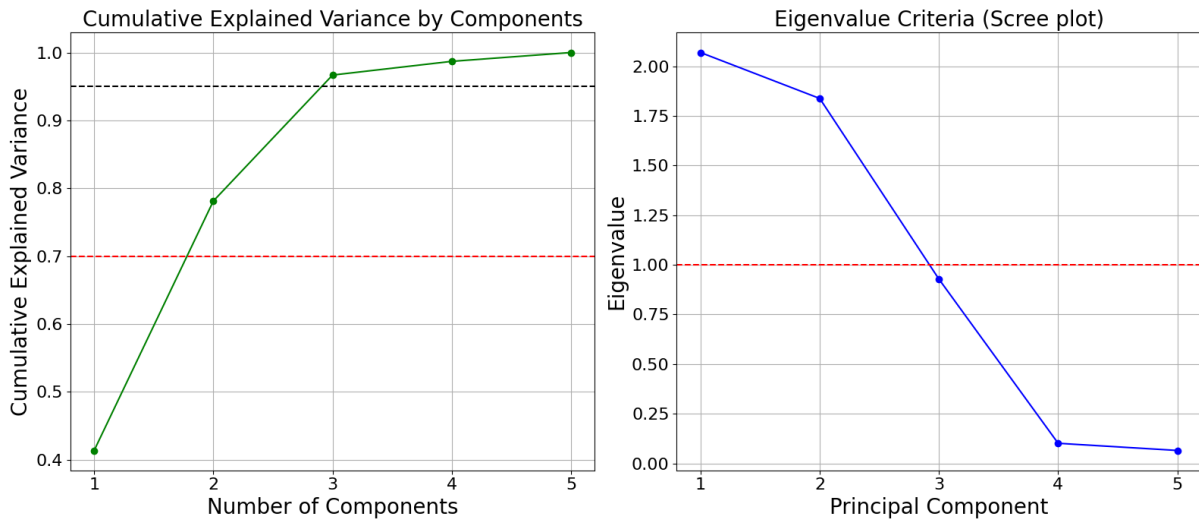


Figure 6.4: Plots for Cumulative Explained Variance and Eigenvalue Criteria

The Cumulative Explained Variance plot shows how much additional variance is captured with each successive principal component. The plot includes critical thresholds marked at 70% (red dashed line) and 90% (black dashed line), which are commonly used to guide the selection of the optimal number of components. These thresholds represent cumulative variance levels that are often considered sufficient to explain most of the variance in the dataset (Jolliffe and Cadima, 2016; Abdi and Williams, 2010). In this case, the elbow point in the curve becomes noticeable after the second component, signalling diminishing returns from adding more components. Specifically, retaining just the first two principal components captures 78.1% of the total variance, striking an effective balance between model simplification and information retention (Jolliffe and Cadima, 2016). Selecting components based on the elbow point ensures that the most informative components are preserved, while avoiding the inclusion of unnecessary ones that contribute minimal variance.

The Scree Plot of Eigenvalues further supports this decision by showing the eigenvalues for each component. The eigenvalues drop below 1 after the second principal component, which

aligns with the Kaiser criterion—a guideline suggesting that only components with eigenvalues greater than 1 should be retained (Kaiser, 1960). This criterion reinforces that the first two components carry the most significant amount of variability in the dataset, and thus, are the most relevant for further analysis.

By retaining these two principal components, the PCA effectively reduces the dataset's dimensionality while maintaining its most critical information (Shlens, 2014). This dimensionality reduction minimizes the risk of overfitting and enhances the robustness and interpretability of subsequent analyses. The simplified dataset, which now retains a high percentage of variance, allows for more efficient analysis in the following sections.

6.4.2 K-means clustering results

K-means clustering requires the number of clusters (K) to be specified in advance. To determine the optimal K, this study evaluates clustering performance using two complementary metrics: the Silhouette Score and the Calinski-Harabasz Index. These measures assess the internal consistency and external separation of clusters, offering quantitative insight into how well the data are partitioned.

Figure 6.5 presents the results of this evaluation across K values ranging from 2 to 10. The left plot displays the Silhouette Score, which measures how similar each data point is to its own cluster compared to other clusters. A higher score indicates better-defined and more cohesive clusters. In this case, the Silhouette Score increases significantly up to $K = 4$, where it reaches its maximum, before gradually declining as K increases further. This suggests that $K = 4$ yields

the most clearly delineated cluster structure, with strong intra-cluster cohesion and minimal overlap between groups.

The right plot shows the Calinski-Harabasz Index, which compares between-cluster dispersion with within-cluster dispersion. A higher index value signifies better-defined clusters. The results show a sharp increase up to $K = 4$, followed by fluctuations with no substantial improvement beyond that point. This again supports $K = 4$ as the most suitable choice, as additional clusters do not significantly enhance clustering performance and may introduce unnecessary complexity.

Together, these two metrics indicate that $K = 4$ represents the optimal balance between model simplicity and clustering effectiveness. The clustering solution at this value provides distinct, well-separated groups, reinforcing the validity of the selected K and demonstrating the model's ability to capture meaningful structure in the data.

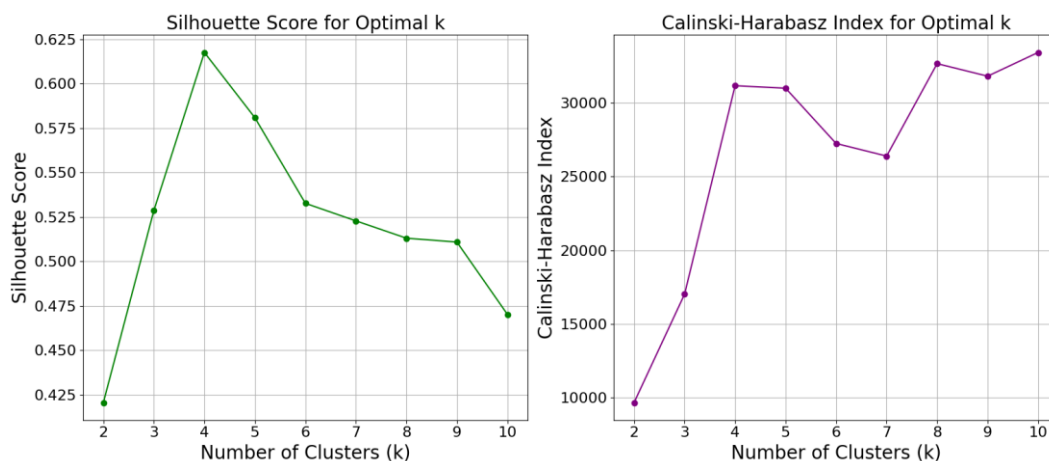


Figure 6.5: Plots for Clustering Quality Metrics: Silhouette and Calinski-Harabasz

Figure 6.6 presents the results of the K-means clustering, visually demonstrating how the algorithm partitions the data into four distinct groups. Using Principal Component Analysis (PCA) to reduce the data to two dimensions, the plot reveals a clear spatial separation between clusters. Each cluster forms a compact and coherent grouping, with minimal overlap, reflecting strong intra-cluster similarity and distinct inter-cluster boundaries. These visual outcomes are consistent with the silhouette analysis, confirming that the selected number of clusters ($K = 4$) effectively captures the underlying structure of the dataset.

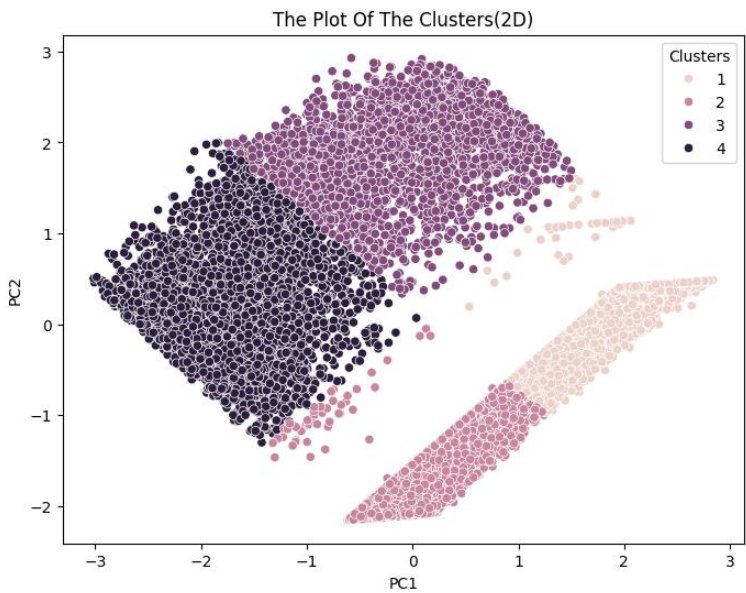


Figure 6.6: Visualisation of K-Means Clustering on PCA-Reduced Data (2D Projection)

Table 6.4 provides a comprehensive summary of descriptive statistics for each of the four identified clusters, offering valuable insights into the characteristics of the data points within each cluster. The table summarizes key statistics for the four bidding clusters that Snipers (1.02 bids) and Early Evaluators (1.01 bids) place fewer bids, while Shooters (3.79) and Participators (4.44) are more active; Snipers have the highest average feedback (316.22), indicating more experience, while Participators have the lowest (105.73); Shooters (10.73) and Participators

(8.86) bid more aggressively compared to Snipers (0.002) and Early Evaluators (0.005); Snipers enter and exit late in auctions, while Early Evaluators and Participators bid earlier in the process. These distinctions are crucial for gaining insights into bidder behaviour and can guide targeted decision-making or further refinement of auction models.

Table 6.4: Descriptive Statistics for Key Clustering Criteria by Cluster

Cluster Dimension	Descriptive Statistics	Cluster 1: (n = 3066)	Cluster 2: (n = 3778)	Cluster 3: (n = 2776)	Cluster 4: (n = 3848)
Number of Bids	Mean	1.0163	1.0127	3.7893	4.4374
	Std	0.1390	0.1120	3.1639	3.5714
	Skewness	10.1048	8.7018	8.6314	3.0311
	Kurtosis	128.7190	73.7212	174.6772	13.0186
Feedback Scores	Mean	316.2202	246.3245	227.2731	105.7318
	Std	693.8567	542.8404	485.9256	302.5477
	Skewness	13.9768	4.3167	7.4662	6.6673
	Kurtosis	401.5717	27.7632	113.0458	63.9502
Average Bid Increment	Mean	0.0017	0.0050	10.7282	8.8562
	Std	0.0338	0.0485	12.1273	12.2651
	Skewness	23.0567	10.1044	4.3011	4.7912
	Kurtosis	584.7097	103.4651	32.1348	37.8637
Time of Entry	Mean	0.8811	0.1496	0.7294	0.1318
	Std	0.1514	0.1431	0.2642	0.1225
	Skewness	-1.0634	1.0911	-0.9010	1.1447
	Kurtosis	-0.2150	0.3123	-0.0846	0.5358
Time of Exit	Mean	0.8814	0.1497	0.8879	0.2162
	Std	0.1513	0.1431	0.1415	0.2047
	Skewness	-1.0650	1.0914	-1.2008	1.3849
	Kurtosis	-0.2117	0.3123	0.2800	1.6910

The clustering results are further explored by analysing the mean values of key features within each cluster. **Figure 6.7** displays these averages, providing a direct comparison of the defining characteristics that differentiate one cluster from another. The visual summary facilitates intuitive comparison, allowing for quick identification of meaningful differences between clusters. These insights serve as a foundation for targeted interpretation and further investigation. A more detailed examination of these cluster-specific attributes is provided in the subsequent sections, where each cluster is described in depth to uncover the unique behavioural profiles and strategic tendencies that characterise the bidders within each group.

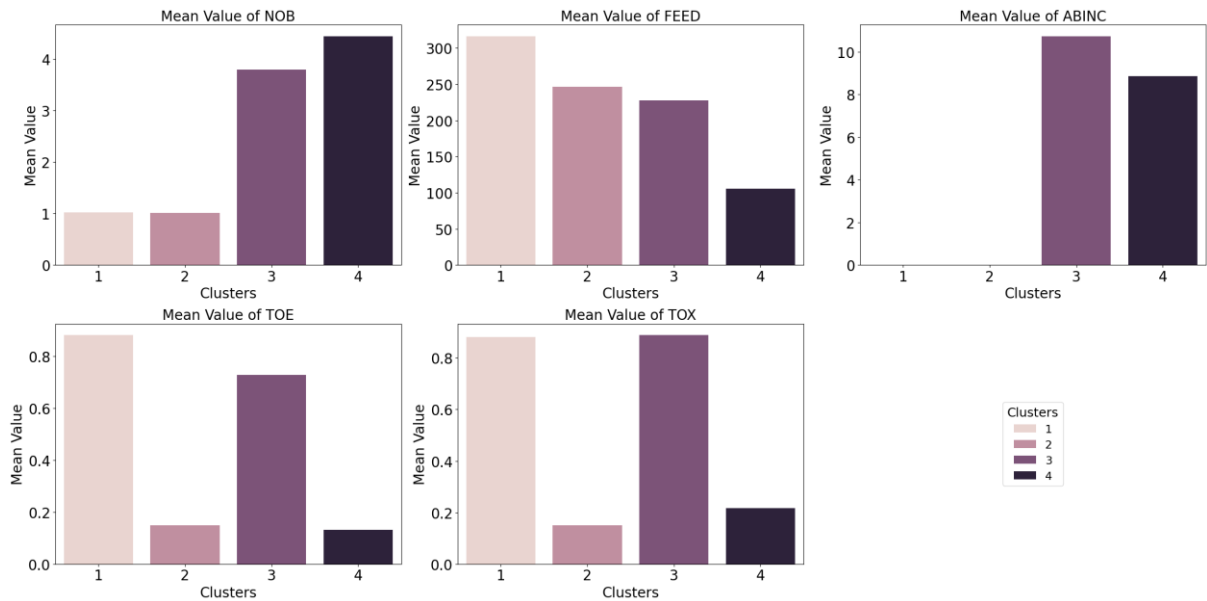


Figure 6.7: Mean Feature Values by Cluster

The characteristics of each cluster are derived from the descriptive statistics presented in **Table 6.4** and the mean feature values illustrated in **Figure 6.7**. These analytical outputs facilitate a comparative interpretation of key behavioural indicators across clusters, revealing distinct bidder profiles within the dataset. Building on these clustering results, the following sections provide an in-detailed examination of each cluster, outlining their unique strategic behaviours.

1) Cluster 1 – Snipers

Cluster 1 exhibits a highly strategic bidding profile. Notably, this group is characterized by very low number of bids (*NOB*: 1.016) and minimal average bid increments, indicating a precise, calculated approach aimed at minimizing price escalation. Participants consistently enter and exit auctions late (*TOE*: 0.881; *TOX*: 0.881), a hallmark of a “sniper” strategy. The highest average feedback score (*FEED*: 316.22) further underscores that experienced bidders are employing a last-minute bidding tactic.

This group is named as Snipers rather than Opportunists. Opportunists typically seek bargains and bid when they perceive a favourable deal, generally placing minimum bids before the auction ends (Bapna, Goes and Gupta, 2000)—a broader approach that does not always mean last-minute bidding (März *et al.*, 2022). In contrast, the observed behaviour aligns more closely with sniping, a tactic well-documented in studies of eBay auctions. Experienced bidders strategically place their bids at the end of the auction to avoid competitive bidding and unnecessary price inflation (Srinivasan and Wang, 2010; Livingston, 2010; Pownall and Wolk, 2013; Feng, Fay and Sivakumar, 2016). The exceptionally high feedback scores indicate that these bidders have built strong reputations and possess significant auction experience, further reinforcing their capacity to execute such precise and calculated strategies. Empirical evidence from prior research (Bapna, Goes and Gupta, 2000, Bapna *et al.*, 2004; Roth and Ockenfels, 2002; Ockenfels and Roth, 2006; Goes, Karuga and Tripathi, 2012) corroborates these observations, confirming that the behavioural profile of Cluster 1 closely mirrors that of Snipers in online auctions.

2) Cluster 2 – Early Evaluators

Cluster 2 is defined by early auction participation, as indicated by early entry (*TOE*: 0.1496) and early exit (*TOX*: 0.1497), combined with minimal bidding activity (*NOB*: 1.0127) and a low average bid increment (*ABIN*: 0.0050), yet with relatively high experience (*FEED*: 246.33). The behavioural pattern observed in Cluster 2 is similar yet opposite to that of Snipers and Participators. Although both Cluster 2 and Snipers feature high average *FEED* values and minimal *NOB* and *ABINC*, their bid timing metrics diverge significantly; Snipers tend to join and exit very late, whereas Early Evaluators engage at the beginning of the auction. This pattern

aligns with the findings of Borle, Boatwright, Kadane (2006), which indicate that experienced bidders often place their bids either at the start or near the end of an auction. Additionally, while Cluster 2 shares early entry and exit characteristics with Participators, the remaining mean values are distinctly different, underscoring a unique strategic approach.

This cluster, labelled as Early Evaluators, aligns closely with the Early Evaluator profile originally proposed by Bapna *et al.* (2004). Bidders in this group enter auction early to assess the auction, submit one or very few bids that reflect their maximum WTP, and then exit promptly. Although Bapna *et al.* (2004) note that bidders may eventually learn to avoid this approach for potentially leaving money on the table, Cluster 2 exhibits relatively high *FEED* values, indicating significant auction experience. In contrast, Borle, Boatwright, Kadane (2006) observe that experienced bidders tend to place their bids either at the beginning or near the end of an auction rather than bidding continuously. This evidence reinforces the distinction between Snipers and Early Evaluators: while both groups demonstrate high *FEED* values, their bidding behaviours are distinctly different.

3) Cluster 3 – Shooters

Cluster 3 is characterized by a mid-entry timing (0.7294) paired with a late exit (0.8879) and the longest overall duration compared to the other clusters. This group exhibits a notably high bidding frequency (3.7893) alongside substantial average bid increments (10.7282). Despite their aggressive bidding behaviour, the feedback scores are relatively lower (227.27), suggesting a lower level of experience among its participants. Their competitive intensity, characterised by high *ABINC* and *NOB*, and prolonged participation are critical in shaping auction dynamics, potentially intensifying competitive biddings and influencing final prices.

While some characteristics, such as frequent bidding and sustained activity until the auction's end, partially overlap with the Sip-and-Dipper or Participator profile described by Bapna *et al.* (2004), the behaviour observed in this cluster more closely aligns with newly labelled Shooters. Their behavioural patterns fall between those of Snipers and Participators. Snipers exhibit late bidding with a minimal number of bids and high experience levels, whereas Participators are characterized by early entry bid, a relatively late final bid (indicating prolonged engagement), and a higher number of bids overall. In the case of Shooters, although they have the longest average auction duration and a similar number of bids as Participators, they tend to enter the auction after the midpoint and continue bidding until later stages, with high average feedback scores resembling the Sniper profile. Moreover, their lower average NOB compared to Cluster 4 (Participators) positions them as an intermediate group. Furthermore, as Goes, Karuga and Tripathi (2012) argue, bidders categorized as Participators often adjust their strategies with increasing experience by shifting to alternative approaches. Therefore, it is more appropriate to designate Cluster 4 as Participators, while Cluster 3 should be recognized as a distinct group with its own unique characteristics.

4) Cluster 4 – Participators

Cluster 4 characterized by early auction engagement, with bidders entering early (*TOE*: 0.132) and exiting shortly thereafter (*TOX*: 0.2162). This group places the highest number of bids (*NOB*: 4.4374) and exhibits substantial average bid increments (*ABINC*: 8.8562), reflecting an aggressive and active bidding strategy during the initial phase of the auction. Notably, the feedback scores are very low (approximately 105.73), suggesting that these bidders generally have less auction experience.

Previous research (Bapna, Goes and Gupta, 2000; Bapna *et al.*, 2004) defined Participators as bidders who enter early and continue a high frequency bidding pattern throughout the auction. Subsequent studies (Bapna *et al.*, 2009; Goes, Karuga and Tripathi, 2012) expanded on this, by describing Participators as those who remain actively engaged over an extended period, placing multiple bids. The decision to label Cluster 4 as Participators is supported by several factors. Although participation duration of Cluster 4 is shorter than that of Cluster 3, it still features a substantial number of bids within a notable timeframe. In contrast to Cluster 3's later time of entry and exit, which suggests a last-minute bidding strategy, Cluster 4 bidders demonstrate relatively early entry, sustained engagement, and high bidding frequency, coupled with lower levels of experience. This pattern is consistent with findings from existing research (e.g., Wilcox, 2000; Simonsohn and Ariely, 2008; Wang and Hu, 2009; Livingston, 2010), which indicate that less experienced bidders tend to bid more intensively when they engage early and remain active.

6.4.3 Explaining the clustering results

This analysis integrates two machine learning techniques, K-means clustering and XGBoost classification, to explore bidder behaviour in remanufactured product auctions. K-means, an unsupervised learning algorithm, identifies natural groupings within the data based on feature similarity. These groupings are then analysed using XGBoost, a powerful supervised classification model, to determine the key features that drive cluster formation. In this framework, the cluster labels generated by K-means serve as the dependent variable, while the original feature set is treated as the independent input.

The dataset was partitioned into training and test sets using an 80:20 split. This configuration demonstrated the highest performance in cross-validation compared to alternative splits of 70:30 and 60:40 (see **Table A.5**), indicating greater internal robustness and model consistency. Although test set performance under the 80:20 split was slightly lower, the superior cross-validation results justified its selection, offering enhanced model generalisability and stability.

To enhance interpretability, SHAP values were computed on the training set to explain the XGBoost model's decisions. SHAP provides both global and local insights by quantifying how each feature influences predictions. A summary plot illustrates the relative importance of features and their directional effects across observations, thereby revealing the key drivers of classification. This approach enables a detailed understanding of the behavioural distinctions among the four identified bidder clusters.

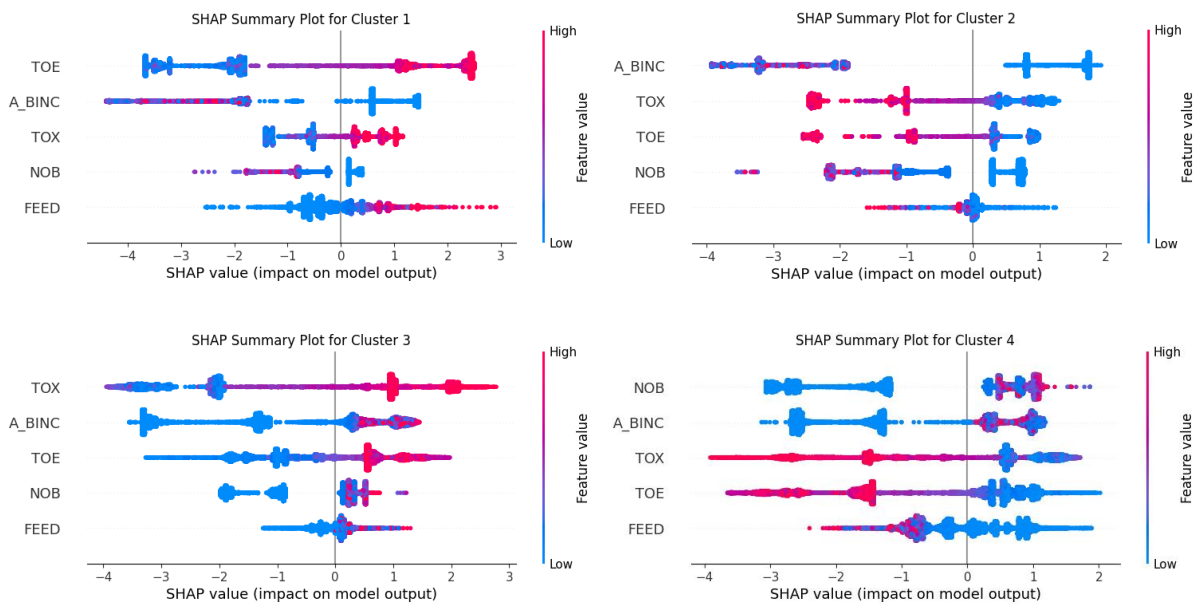


Figure 6.8: SHAP Beeswarm Summary Plots by Cluster

1) Cluster 1 – Snipers

As shown in **Figure 6.8**, Cluster 1 is characterized by very late entry and exit, a minimal number of bids, the highest feedback score, and small price increments per bid. This cluster aligns with the Sniper or Opportunist strategy, as described by previous studies (e.g., Bapna, Goes and Gupta, 2000; Roth and Ockenfels, 2002; Shah *et al.*, 2003; Bapna *et al.*, 2004; Shang, Chen and Cheng, 2006) and. The bidding behaviour in this cluster highlights the impact of experience, with numerous studies showing that experienced bidders are more likely to place bids closer to the auction's end, rather than making multiple early bids (e.g., Wilcox, 2000; Roth and Ockenfels, 2002; Ockenfels and Roth, 2006; Wang and Hu, 2009; Livingston, 2010).

The SHAP summary plot for Cluster 1 in **Figure 6.8** highlights the key factors influencing Cluster 1's behaviour: Time of Exit (*TOE*), Average Bid Increment (*ABINC*), Feedback Scores (*FEED*), Time of Entry (*TOX*), and Number of Bids (*NOB*). Higher *TOE* values, representing late exits, have a strong positive impact on predictions, reinforcing the Sniper strategy, where bidders aim to gain an advantage by bidding at the last moment. Similarly, *TOX* shows that snipers not only exit late but also enter auctions late, further emphasizing their last-minute bidding approach. *ABINC* is also significant, with lower values indicating a preference for small, strategic price increments, consistent with the sniper's careful approach. Although *NOB* and *FEED* are less influential, lower *NOB* positively impacts the model's predictions toward Cluster 1, suggesting that snipers tend to place fewer bids. Meanwhile, higher *FEED* values positively influence predictions, indicating that more experienced bidders are often classified as snipers.

2) Cluster 2 – Early Evaluator

Cluster 2 can be described as Early Evaluators, characterized by minimal bidding activity, early entry, and early exit, closely matching the profile proposed by Bapna *et al.* (2004). Participants in this cluster engage soon after the auction begins, placing only one or very few bids before exiting, resulting in brief participation and fewer total bids. This behaviour is typically linked to higher feedback scores, in line with Borle, Boatwright and Kadane (2006), who noted that experienced bidders are more likely to place bids either at the start or end of an auction, rather than participating mid-way. Additionally, more experienced bidders tend to engage less in multiple bidding.

The SHAP summary plot for Cluster 2 in **Figure 6.8** highlights the key features influencing the model's predictions for this group. Average Bid Increment (*ABINC*) is the most significant factor, with lower values (smaller average price increases) having a strong impact on predictions. This suggests that members of Cluster 2 tend to place lower bids relative to the previous price, reflecting cautious behaviour. Time of Exit (*TOX*) is another critical feature, with low *TOX* values (early exits) contributing heavily to the classification of bidders in this cluster. This supports the idea that Cluster 2 members exit auctions quickly after entering. Time of Entry (*TOE*), with low values indicating early entry, further confirms that these bidders typically engage early in the auction process. Additionally, Number of Bids (*NOB*) plays a significant role, with low *NOB* values reinforcing the minimal bidding activity observed in this cluster. Lastly, Feedback Scores (*FEED*), while less influential, still contribute to predictions, with lower feedback scores mildly affecting the model's output.

3) Cluster 3 – Shooter

Cluster 3 is defined by mid-entry and late-exit behaviour (long duration), lower feedback scores (less experience), significant average bid increment, and the highest bidding activity, as shown in **Figure 6.8**. While some traits, such as high number of bids and late exit, resemble the Sip-and-Dipper profile from Bapna *et al.* (2004), Cluster 3 more closely fits a new bidder type, which named it as Shooter. Members of this group join later, similar to Snipers, but differ in their active participation throughout the auction. Shooters place frequent bids and have a notable impact on driving up prices. This combination of mid-entry, sustained bidding, and price influence makes Shooters a distinct and influential presence, setting them apart from both passive and last-minute bidders.

The SHAP analysis highlights several key features that define Cluster 3. Among these, *TOX* is the most influential, with higher values (indicating later exits) strongly impacting the model's predictions. *ABINC*, which reflects steady price increases with each bid, also has a positive effect, indicating that Cluster 3 members tend to raise bids many on average. Higher *TOE* values increase the likelihood of being classified in Cluster 3, reinforcing the observation that these bidders typically join auctions later, showing strategic behaviour. *NOB* is another important factor, with higher values indicating more frequent bidding, suggesting active involvement throughout the auction. While *FEED* plays a smaller role, slight variations in feedback scores still influence the model's predictions.

4) Cluster 4 – Participators

Cluster 4 demonstrates several distinctive characteristics based on **Figure 6.8**. The lower mean *TOE* value and the low mean *TOX* value indicates that they enter early and exit early but relatively long duration compared to other clusters. This behaviour is similar to the Participator archetype described by Bapna *et al.* (2004), though unlike Participators, Cluster 4 exits earlier in the auction. Cluster 4 also stands out for placing the highest number of bids, signalling high activity with frequent incremental bidding. Furthermore, this cluster has the lowest feedback score, indicating less experience on the auction platform compared to other clusters. When compared to Cluster 3 (Shooters), participants in Cluster 4 remain active during the early auction stages, placing more bids with smaller price increments per bid. This behaviour reflects a cautious bidding strategy, marked by frequent but modest price increases early on.

The SHAP summary plot for Cluster 4 highlights *NOB* as the most influential factor, with higher values indicating more bids, which positively impact the model's predictions. *ABINC* is another key factor, where higher values suggest larger price increments per bid, also contributing positively to the model's predictions. Lower *TOX* and lower *TOE* are significant features, indicating that Cluster 4 participants are more likely to enter auctions early and exit early. Although lower *FEED* values contribute positively, their overall effect on Cluster 4's behaviour remains minimal.

According to the findings from clustering and applying SHAP analysis, the results provide more detailed explanations of how the features influence the different clusters. SHAP analysis enables a deeper understanding of the impact of features on the output, making it clear how each feature contributes to the formation and characteristics of each cluster. Some cluster

profiles align well with previous studies, confirming existing theories and observations. However, other clusters show distinct behaviours and characteristics that differ significantly from the existing literature, offering fresh insights.

This discrepancy is a major contribution of this study to the relevant literature, as it not only validates known bidder profiles but also uncovers new patterns of behaviour that were previously unexplored. These findings can inform future research and practical applications, such as developing more targeted bidding strategies or enhancing auction platform designs to accommodate diverse bidder types. By providing a deeper understanding of bidder behaviour, this study adds depth to the field and opens up new avenues for investigation and application.

6.4.4 Outcome Analysis

Given the evident heterogeneity in bidding behaviour, it is essential to analyse the impact of these different strategies on both the likelihood of winning and the resulting consumer surplus. The analysis further examines the performance of distinct bidder groups in auctions, with a specific focus on their likelihood of winning and the revenue generated from successful bids. Bapna, Goes and Gupta (2000) provided the first empirical classification of individual bidding patterns in online environments, yielding valuable insights on comparing revenues across various auction formats. Subsequently, Bapna *et al.* (2004) established a robust taxonomy of bidder behaviour that identifies five distinct bidding strategies, varying probabilities of winning and differing levels of surplus. Building on these foundational studies, the present analysis deepens the understanding of how heterogeneity in bidder behaviour can enhance both the likelihood of winning and the overall profitability of auction strategies.

6.4.4.1 Winning Percentage

Building on the outcome analysis used by Bapna *et al.* (2004), the initial focus is on determining whether varying bidding strategies influenced winning percentages across clusters. To test this, a single-factor ANOVA was performed on the four clusters representing different bidding strategies, assessing whether statistically significant differences in winning likelihood existed among these groups. Hypothesis 1 (H1) posits:

H1: There is no significant difference in the likelihood of winning across all bidder classes, as reflected in the proportion of winners versus losers.

The method for calculating the winning percentage is straightforward—it reflects the proportion of auctions won out of all the bids in which the cluster participated. **Table 6.5** presents the one-way ANOVA results, which compare the winning percentages across four distinct bidding strategies: Snipers, Shooters, Participators, and Early Evaluators. With an F-value of 637.989 and a highly significant p-value (< 0.001), the null hypothesis can be rejected, confirming that the mean winning percentages differ significantly among these bidder types.

Table 6.5: One-way ANOVA Summary: Winning Proportions by Clusters

Source of Variation	SS	df	MS	F	P-value
Between Groups	247.0338	3	82.3446	637.9893	0.0
Within Groups	475.5838	13464	0.0353		
Total	722.6176	13467			

Further pairwise comparisons were conducted to assess differences in winning percentages between each bidder type. To control for Type I errors arising from multiple comparisons, the Bonferroni correction was applied, adjusting significance levels by dividing by the number of

comparisons ($m = 6$). This approach upholds statistical rigour while managing the family-wise error rate. **Table 6.6** presents the results of these pairwise comparisons, displaying the t-values for differences in winning percentages across each pair of bidding strategies. Each comparison yielded statistically significant differences, marked with asterisks (*), signifying that each bidding strategy leads to distinct success rates.

Table 6.6: Pairwise Comparison of Winning Proportions Across Clusters

t value (Average winning %)	Cluster Name			
	Participators (4.2%)	Snipers	Early Evaluators	Shooters
Snipers (62.4%)	33.46***			
Early Evaluators (0.6%)	-5.03***	37.83***		
Shooters (41.6%)	21.22***	9.04***	-24.70***	

Table 6.7 presents the number of bidders and winners for each cluster, along with the win ratio for each group. In the Sniper cluster, 564 out of 904 items (62.4%) became winners, while 377 out of 906 bidders (41.6%) won in the Shooter cluster. In contrast, the Early Evaluator and Participator clusters show significantly lower chances of winning compared to these two groups.

Table 6.7: Winning Possibilities by Cluster

	Cluster Name			
	Snipers	Early Evaluators	Shooters	Participators
No. of Winnings	564	6	377	39
No. of Participations	904	945	906	935
Ratio	0.623894	0.006349	0.416115	0.041711

These pairwise comparisons and winning ratio clearly show that Snipers consistently achieve the highest success rates, followed by Shooters, while Participators and Early Evaluators are far less successful. The significant t-values in **Table 6.7** demonstrate that each bidding strategy results in distinct winning outcomes, reinforcing the importance of the chosen bidding approach.

This analysis underscores the critical role of bidding strategies in determining auction success. Snipers, who enter auctions late and place targeted bids, have the highest winning percentage, followed by Shooters, who actively participate but with less precision. Participators and Early Evaluators have the lowest likelihood of winning, suggesting that these strategies are less effective. The results provide strong evidence that certain strategies are far superior for achieving success in online auctions.

6.4.4.2 Loss of Surplus

Following the analysis of winning probabilities across various bidder clusters, the focus shifts to understanding how surplus generation differs by cluster membership. To investigate this, the hypothesis was tested that all bidding strategies yield an equivalent level of normalised surplus loss. Specifically, **Hypothesis 2 (H2)** posits:

H2: All clusters have the same level of normalized loss of surplus.

Normalized loss of surplus is calculated as:

$$\text{Normalized loss of surplus} = \frac{\text{Winning Price} - \text{Marginal Price}}{\text{Marginal Price}}$$

where the marginal price represents the lowest winning price in an auction. This metric evaluates how much money each bidder leaves “on the table” by comparing their winning bid to the marginal price, reflecting the surplus they could have maximized by bidding closer to the marginal price. In Yankee auctions, where each winner pays their own price, this calculation becomes essential for understanding how efficiently different strategies create surplus.

An ANOVA was conducted to compare the mean normalized loss of surplus across different bidding strategies. As shown in **Table 6.8**, the results indicate a significant difference in the normalized loss of surplus between the four bidding strategies ($F = 11.95$, $p < 0.0001$). This shows that bidders employing different strategies experience varying levels of surplus loss, meaning their efficiency in maximizing surplus differs significantly.

Table 6.8: One-way ANOVA Summary: Normalised Loss of Surplus by Clusters

Source of Variation	SS	df	MS	F	P-value
Between Groups	5.1552	3	1.7184	11.9537	1.084109e-07
Within Groups	141.1677	982	0.1438		
Total	146.3230	985			

Moreover, the pairwise comparisons presented in **Table 6.9** indicate that the Sniper and Shooter clusters exhibit the most significant difference in maximizing surplus. In contrast, no statistically significant differences were found in the other pairwise comparisons. As shown in **Table 6.9**, this can be attributed to the fact that the Sniper and Shooter clusters have a relatively large number of winning bidders, while the Participator and Early Evaluator clusters have significantly fewer samples. The lack of statistical significance in some pairwise comparisons may be due to insufficient sample sizes, making it difficult to detect meaningful differences.

Table 6.9. Pairwise Comparison of Normalised Loss of Surplus Among Clusters

t value (Average winning %)	Cluster Name			
	Participators (0.4%)	Snipers	Early Evaluators	Shooters
Snipers (18.4%)	-2.22			
Early Evaluators (0.2%)	1.74	-2.59		
Shooters (13.6%)	-0.67	-4.43***	2.06	

Beyond the primary analysis, an additional examination was conducted on the mean values of surplus normalized loss. Bapna *et al.* (2004) refer to the excess amount paid above the marginal

price as the “money on the table.” **Table 6.10** presents the descriptive statistics for surplus loss across various clusters. The Sniper cluster displays the lowest loss of surplus (0.481), indicating that the difference between their winning bid and the lowest possible winning price is approximately half of that lowest price. In comparison, the Shooter and Participator clusters show slightly higher surplus loss values (0.596 and 0.648), though still relatively close to the Snipers. However, the Early Evaluator cluster exhibits significantly less efficient bidding behaviour, with a surplus loss exceeding 1, meaning their bids are, on average, twice as high as the lowest winning price. This indicates a considerable inefficiency in their bidding strategy.

Table 6.10. Normalised Loss of Surplus by Cluster

Cluster	Cluster Name			
	Snipers	Early Evaluators	Shooters	Participators
Count	564	6	377	39
Mean	0.480846	1.050961	0.596111	0.647775
Std	0.338306	0.53788	0.422887	0.460091
Max	2.424528	2.061321	4.679136	2.125
Min	0	0.631356	0	0.071429

These findings underscore the critical role bidding strategies play in shaping auction outcomes. Sniping, where bids are placed near the end of the auction at prices close to the marginal price, emerges as the most effective strategy, both for increasing chances of winning auctions and maximizing surplus. In contrast, early evaluation, where bidders place early and often high bids, leads to inefficiencies and greater surplus loss. Additionally, the Shooter cluster, which shares similarities with the Sniper strategy, also performs quite well. While there are differences, such as feedback scores and the number of bids placed, Shooters seem to adopt a similar approach to Snipers, resulting in notable success in both increasing their chances of winning and maximizing surplus.

6.4.4.3 Winning Efficiency

While the concept of Loss of Surplus was used to quantify the additional amount a bidder paid compared to the lowest winning price, a question arises as to whether the lowest price accurately represents bidding efficiency. To explore this issue, an alternative metric, Winning Efficiency, is introduced to provide a different perspective on efficiency in auction outcomes. Winning Efficiency measures how much a bidder's final price deviates from the average auction price, offering a relative assessment of bidder efficiency. It is calculated by taking the difference between the winning price and the average price, then normalising this difference by the average price. A negative value indicates a more efficient win (i.e., below-average price), while a positive value suggests the bidder paid a premium. The formula is:

$$\text{Winning Efficiency} = \frac{\text{Winning Price} - \text{Average Price}}{\text{Average Price}}$$

To assess whether different bidding strategies lead to significantly different levels of Winning Efficiency, an ANOVA test was conducted, revealing a statistically significant variation across strategies, as shown in **Table 6.11** ($F = 11.59$, $p < 0.0001$). This indicates that the efficiency of different strategies in winning auctions is not uniform across the groups, allowing us to reject the null hypothesis and conclude that significant differences exist. The significant F-value shows that the winning efficiency varies significantly across the different bidding strategies. To further investigate these differences, pairwise comparisons were conducted.

Table 6.11. One-way ANOVA Summary for Winning Efficiency by Clusters

Source of Variation	SS	df	MS	F	P-value
Between Groups	1.3713	3	0.4571	11.5928	1.802956e-07
Within Groups	38.7209	982	0.0394		
Total	40.0922	985			

Table 6.12 shows that the Sniper cluster stands out with significantly higher winning efficiency compared to the Early Evaluator ($t = -2.91^*$) and Shooter ($t = -4.55^{***}$) clusters, indicating that Snipers are much more efficient. In contrast, other comparisons, like those involving the Participator and Shooter clusters, show no significant differences, suggesting similar levels of efficiency between them.

Table 6.12: Pairwise Comparison of Winning Efficiency Among Clusters

t value (Average winning %)	Cluster Name			
	Participators (0.4%)	Snipers	Early Evaluators	Shooters
Snipers (18.4%)	-2.91*			
Early Evaluators (0.2%)	0.65	-2,51		
Shooters (13.6%)	-1.26	-4.55***	1.53	

More specifically, **Table 6.13** illustrates the winning efficiency of each cluster. Sniper winners, with a mean value of -0.03, paid 3% less than the average auction price, making their bidding strategy the most efficient compared to the other clusters, all of which exhibit positive values. Shooter winners paid an additional 3% above the average price, while Early Evaluators overpaid by 8.7%. The least efficient group, the Participators, paid 13.8% more than the average. These results highlight the superior efficiency of Sniper strategies in minimizing surplus loss.

Table 6.13: Winning Efficiency by Cluster

Cluster	Cluster Name			
	Snipers	Early Evaluators	Shooters	Participators
Count	564	6	377	39
Mean	-0.030376	0.137491	0.034256	0.086989
Std	0.156141	0.16285	0.24467	0.248868
Max	0.791601	0.30368	2.993219	0.831977
Min	-0.496525	-0.075974	-0.574144	-0.16295

These findings on winning probabilities and surplus emphasize the critical role of bid management and timing in competitive auctions. Snipers who place fewer but well-timed bids,

consistently outperform other bidder types in both metrics. The results align with previous research, which confirms that Snipers, due to their strategic late bidding, achieve superior profits (Ely and Hossain, 2009) and higher winning probabilities (Ely and Hossain, 2009; Gönül and Leszczyc, 2011). In contrast, Early Evaluators and Participators, who place bids earlier or continuously throughout the auction, tend to pay higher prices, reducing their bidding efficiency.

On the other hand, the Shooter cluster outperforms Early Evaluators and Participators in terms of both win rates and surplus metrics. Their Loss of Surplus and Winning Efficiency are second only to the Snipers, suggesting that Shooters are more experienced and efficient in their bidding approach. Unlike Participators, who tend to enter and exit early in the auction and place numerous bids with little experience, Shooters are gradually adopting strategies similar to Snipers, leading to greater efficiency and profitability. For participants looking to improve their auction performance, adopting a Sniper-like strategy could offer significant benefits, maximizing efficiency and minimizing the risk of overpaying.

6.5 Discussion and Managerial Implications

This study identifies four distinct bidding behaviours in online auctions—Snipers, Early Evaluators, Shooters, and Participators—using an integrated explainable ML framework. The approach combines K-means clustering, XGBoost classification, and SHAP analysis to provide interpretable groupings and a clear understanding of how different behavioural profiles impact auction outcomes.

Snipers are characterised by precise, low-frequency bidding concentrated at the very end of the auction. This group exhibits the highest win rate at 62.4% and the lowest surplus loss at 0.48,

indicating that they consistently pay close to the marginal price. In terms of efficiency, Snipers also outperform all other groups by paying approximately 3% less than the average auction price. Their strategic advantage is supported by high feedback scores, suggesting that experience enables effective timing and minimal price escalation.

Shooters adopt a hybrid strategy that involves entering the auction during mid-stages, maintaining high bidding frequency (mean of 3.79 bids), and remaining active until the later phases. Though less efficient than Snipers, Shooters perform strongly overall, with a win rate of 41.6% and a moderate surplus loss of 0.60. Their behaviour reflects a calculated form of aggressive bidding that, when coupled with adequate timing, proves to be relatively effective.

Participators demonstrate high engagement with low returns. They place the highest number of bids (mean of 4.44) but achieve only a 4.2% win rate. Furthermore, they tend to overpay, with a winning price 13.8% above the auction average, indicating substantial inefficiency. Their pattern of early entry, sustained bidding, and low feedback scores suggests a lack of strategy and limited experience, which undermines their effectiveness despite active participation.

Early Evaluators perform the weakest among the four clusters. They enter and exit auctions early, place very few bids, and demonstrate an extremely low win rate of 0.6%. When they do win, their winning price exceeds the average by 8.7%, reflecting poor efficiency. This behaviour likely stems from a fixed valuation mindset where bids are placed early based on a predetermined WTP, regardless of auction dynamics.

Overall, these findings reinforce the importance of timing and behavioural discipline in online auctions for remanufactured products. Success depends less on bidding frequency and more on strategically timed actions. This study makes three key contributions to the literature on bidder heterogeneity in remanufactured product markets. First, it identifies a previously unrecognised bidder type, Shooters, which blends features of Sniping and Participating strategies. Second, by employing explainable supervised clustering, it reveals the contributions of features that shape cluster membership, enhancing interpretability. Third, this is the first empirical study to classify bidder types using auction data for remanufactured products, offering novel insights into behavioural segmentation in markets with information asymmetry and quality uncertainty.

Managerial Implications

Based on the empirical findings, the following managerial implications are proposed to enhance platform effectiveness and bidder outcomes.

1) Tailored Engagement for Distinct Bidder Profiles

Recognising the distinct behavioural profiles—namely, Snipers, Shooters, Participators, and Early Evaluators—allows platforms to customise their communication and engagement strategies. For example, Snipers, who rely on precision bidding and last-minute actions, would benefit from advanced tools such as precise bid timing alerts and automated bid placement features. In contrast, Shooters and Participators, who tend to engage earlier and bid more actively, might respond more favourably to real-time auction dynamics, including live updates and dynamic bidding incentives. Customising user interfaces and notifications to mirror each bidder's strategic approach can foster more effective bidding behaviour and ultimately improve auction performance. In addition, offering fixed-price recommendations for similar products

when an auction is lost could provide bidders with alternative purchasing options, further enhancing the overall user experience.

2) Enhancing Bidder Competence through Education

The study demonstrates that less experienced bidders, especially those identified as Participators and Early Evaluators, often employ strategies that lead to suboptimal outcomes. To address this issue, auction platforms should develop comprehensive educational initiatives aimed at improving bidding efficiency. This could include interactive tutorials, AI-powered chatbots that explain the benefits of strategic bid timing and incremental bidding, and other detailed instructional content. By equipping users with practical knowledge and actionable insights, platforms can help these bidders refine their strategies, thereby improving individual outcomes and fostering a more dynamic auction environment.

3) Personalised User Experience:

Detailed cluster analysis offers significant opportunities to personalise the user experience. Auction sites can leverage insights from bidder segmentation to recommend specific auction types, optimal bid increments, and interface configurations that are tailored to individual user profiles. For instance, a personalised dashboard that reflects historical bidding performance and suggests strategic adjustments could significantly enhance user engagement and satisfaction. By delivering a bespoke experience, platforms not only improve bidder outcomes but also encourage higher levels of participation, ultimately driving increased auction revenues.

Chapter 7

Conclusions and Future Work

7.1 Introduction

This concluding chapter synthesises the principal findings of the thesis within the context of existing literature, evaluating the extent to which the research objectives and questions articulated at the outset have been addressed. The chapter is structured as follows. Section 7.1 provides a comprehensive summary of the key empirical insights derived from the study, aligning them with the core research questions. Section 7.2 outlines the ethical considerations observed throughout the research process. Section 7.3 articulates the contributions made to the literature on closed-loop supply chains (CLSCs) and related domains. Finally, Section 7.4 identifies the limitations of the study and proposes future research directions that build upon the work presented in this thesis.

7.2 Research Questions and Main Findings of the Study

The ultimate goal of this paper is to advance the insights that facilitate the operationalization of the remanufactured product market by exploring the market factors influencing final auction price, seller behaviours and strategies based on different remanufactured product conditions, and bidder actions and strategies in auctions. The focus of this study is justified by the gaps in existing empirical research on remanufactured products, which lacks analysis specific to

auction markets and offers limited examination of seller strategies and bidder behaviours, particularly for remanufactured items across varying conditions. In this section, the main findings of this research are summarized in relation to the key research questions:

Research Question 1: How do market signals from sellers, buyers, and the platform influence final auction prices for remanufactured electronics?

This study addresses this question by combining ML with explainable artificial intelligence (XAI) to analyse how multi-actor market signals shape auction outcomes for remanufactured electronics. While prior studies have examined price determinants using traditional LR models and secondary transaction data (e.g., Subramanian and Subramanyam, 2012; Pang *et al.*, 2015; Frota Neto, Bloemhof and Corbett, 2016; Zhou and Gupta, 2019, 2020), they fall short in capturing the non-linear and interactive effects that characterise auction markets. More recent work by Van Nguyen *et al.* (2020) demonstrated the predictive advantages of ML, but the interpretability of their findings was constrained by reliance on global summary tools such as variable importance rankings and partial dependence plots.

To address this gap, the present study integrates SHAP with ensemble learning models to improve both predictive performance and model transparency. SHAP not only quantifies global feature importance but also explains individual predictions, enabling the identification of threshold effects and non-linear interactions. The analysis focuses on key market signals, including starting price, number of bids, feedback scores, and number of product images, and reveals several insights overlooked in prior research, identifying an asymmetric effect of recent feedback. Lower feedback scores are associated with higher final prices, whereas higher scores beyond a threshold reduce predicted prices. This suggests a more complex interpretation of

reputation signals in the context of remanufactured products, where buyers may value transparency or perceive over-reputation as linked to lower product quality. Such dynamics are particularly salient in markets characterised by information asymmetry and heterogeneous product conditions. By extending the methodological toolkit with XAI, this study contributes to auction theory, remanufactured goods pricing literature, and the broader application of XAI in digital marketplaces.

Research Question 2: How do auction prices and market signal effects and seller strategies vary with by the condition level of remanufactured products in online auctions?

This study advances the literature by investigating how granular product condition tiers influence pricing dynamics, signal effectiveness, and seller strategies in online auctions of remanufactured goods—a dimension that remains largely underexplored. While prior research has examined price differentials between new and remanufactured products or WTP between broad product categories (e.g., new, remanufactured and used) (Subramanian and Subramanyam, 2012; Pang *et al.*, 2015; Frota Neto, Bloemhof and Corbett, 2016; Xu, Zeng and He, 2017), it has not systematically accounted for intra-category condition distinctions. This omission is significant, given that digital platforms like eBay classify remanufactured condition into Good, Very Good, and Excellent that buyers rely on to assess quality and risk.

To address this gap, the study empirically examines auction performance across three condition levels using a segmented analysis framework. The findings reveal clear behavioural and strategic differentiation. Items in Excellent condition tend to be sold by less experienced sellers who adopt low starting prices, shorter durations, and rely heavily on sentiment-rich descriptions and visual detail. These strategies correlate with heightened bidding activity and premium final

prices. In contrast, sellers of Good condition products, often more experienced, set higher starting prices and longer durations but see reduced engagement and lower price outcomes, suggesting diminished buyer responsiveness to conventional signalling.

Importantly, this study employs SHAP-based interpretability techniques to identify how the importance of market signals shifts across condition levels. For higher-quality items, affective cues such as sentiment and visual presentation are among the most influential price determinants. Conversely, in lower-quality tiers, more functional variables, such as starting price, bid count and historical sales data, exert greater influence, indicating that buyers adjust their decision heuristics based on perceived product condition.

By integrating condition-specific behavioural analysis with explainable ML, this study introduces a more nuanced model of pricing behaviour in remanufactured product markets. It highlights that market signals are not universally effective but contextually contingent, offering practical insights for sellers and platforms and advancing theoretical understanding of signal–response dynamics in condition-stratified markets.

Research Question 3: What bidding strategies do bidders adopt in remanufactured product auctions?

Previous research has shown that bidder behaviour is heterogeneous across auction contexts. The typology by Bapna *et al.* (2004), identifying profiles such as early evaluators, participants, sip-and-dippers and opportunists, has shaped much of the auction literature. However, these classifications have not been applied to remanufactured product auctions, where concerns over quality and risk perception are more pronounced.

This study is the first to examine bidder heterogeneity in remanufactured goods auctions. By extending Bapna *et al.*'s framework and introducing two additional behavioural dimensions—bid increment and seller feedback—a new bidder type was uncovered: the Shooter. This group, positioned between Snipers and Participators, is defined by mid-to-late entry, high bidding frequency, and relatively large bid increments. Despite having lower feedback than Snipers, Shooters achieved a 41.6% win rate, indicating that timely, assertive bidding can be effective.

Across all bidder types, strategic timing and discipline clearly influenced performance. Snipers were the most efficient, achieving the highest win rate (62.4%) and lowest surplus loss. In contrast, Participators overbid and were least efficient, while Early Evaluators performed worst in terms of win rate and price efficiency. These findings highlight that success in remanufactured product auctions depends more on behavioural precision than bid volume.

To improve interpretability, the study applied explainable AI by reframing clustering as a classification task using XGBoost and SHAP. Key features—entry/exit time, bid count, increment size, and feedback—were identified as primary drivers of bidder type. This methodology not only enhances transparency but also offers a replicable framework for studying auction behaviour in high-uncertainty, remanufactured markets.

7.3 Research Ethics

This study rigorously addresses ethical considerations, highlighting the critical importance of adhering to ethical standards and principles in research. The commitment to ethics is not merely a procedural formality but a foundational pillar that emphasizes on ethics is not just procedural but fundamental, enhancing the research's integrity, credibility, and societal value. Prioritizing the rights and welfare of participants and stakeholders demonstrates the highest standards of ethical responsibility and academic integrity. The study's ethical rigour is evidenced by its strict compliance with the University of Birmingham's ethical framework. The thorough preparation and submission of an ethical review application underscore the research's commitment to transparency and accountability, ensuring all ethical considerations are thoroughly examined and addressed.

This research, which analyses remanufactured products on e-commerce platforms, involves minimal risk due to the absence of live subjects or animals and the low potential for harm. Despite the reduced ethical complexities, the study maintains high ethical diligence. The full ethical endorsement by the University of Birmingham's Humanities and Social Sciences Ethical Review Committee attests to the thoroughness and conscientiousness of the ethical review.

Ethical considerations extend to data usage, particularly adherence to eBay's license agreement. This ensures respect for privacy rights and compliance with legal standards regarding data protection and copyright laws, preventing unauthorized disclosure of information and the collection of copyrighted materials, thereby upholding the integrity and rights of content creators. Data security is addressed through robust measures to protect sensitive information, with encrypted storage exemplifying stringent security protocols against unauthorized access.

The study's ethical foresight is further demonstrated by the plan to responsibly dismantle the dataset after a specified period, adhering to evolving data protection regulations and showcasing a commitment to ethical stewardship and responsible data management.

7.4 Contributions

This section outlines the theoretical and empirical contributions of the thesis by directly addressing the research gaps identified in Chapter 2. Each contribution corresponds to a specific deficiency in prior literature and demonstrates how this study advances the current understanding of remanufactured product auctions and broader auction dynamics.

The first major contribution of this research lies in addressing the fragmented understanding of how diverse market signals, emitted not only by sellers but also by buyers and platform-level mechanisms, jointly shape price outcomes in auction-based markets for remanufactured goods. Previous studies have largely examined isolated signal types, typically focusing on seller reputation or product features, often within fixed-price contexts (e.g., Subramanian and Subramanyam, 2012; Frota Neto *et al.*, 2016; Xu *et al.*, 2017). While Van Nguyen *et al.* (2020) demonstrated that ML could outperform LR models in forecasting remanufactured product demand, their approach fell short in model interpretability, relying on simplified tools such as variable importance rankings and partial dependence plots.

This thesis builds on and extends that line of work by offering a more integrated, multi-actor framework that incorporates buyer-, seller-, and platform-level signals simultaneously. Using ensemble ML models (XGBoost, Random Forest) and SHAP for interpretability, the study not only improves predictive accuracy but also reveals the conditional, non-linear, and interaction-

driven nature of signal effects. For example, the study shows that feedback effects are not uniform: low recent feedback scores may positively impact final prices, while higher scores beyond a certain threshold yield diminishing or even negative returns. Furthermore, the interaction between starting price and seller feedback illustrates how the effectiveness of pricing strategies depends on the seller's reputation level.

By accounting for these interdependencies, the study moves beyond the assumption of linear, context-invariant relationships that have dominated prior auction and remanufacturing research. It contributes to auction theory by identifying critical behavioural thresholds, such as bid count tipping points, minimum photo counts and optimal starting prices, that directly influence buyer engagement and WTP. These empirically validated thresholds offer concrete guidance for platform design and seller strategy, particularly in high-asymmetry markets like those involving remanufactured goods. Additionally, by highlighting how signal importance varies across different listings and user contexts, the study lays groundwork for more personalised and adaptive auction support systems.

The second contribution addresses the underexplored role of intra-category condition variation within the remanufactured product segment. While previous literature has examined consumer valuation differences across broad product categories, such as new, used and remanufactured goods, little attention has been paid to the internal heterogeneity within the remanufactured category itself (Guide and Li, 2010; Pang *et al.*, 2015; Zhou and Gupta, 2020). As a result, much of the existing research fails to capture how finer condition distinctions, commonly employed by platforms like eBay (e.g., Excellent, Very Good, Good), affect pricing dynamics and strategic behaviour in auctions.

This study fills that gap by constructing a condition-segmented dataset that enables condition-specific modelling of auction outcomes. The findings demonstrate that remanufactured product condition not only affects final price levels, but also fundamentally alters the relative importance and effectiveness of market signals. For high-condition products (Excellent), emotional and aesthetic signals, such as sentiment-laden descriptions and image count, are key determinants of perceived value. In contrast, for lower-condition products (Good), buyers rely more on functional signals such as starting price, historical sales and seller feedback. This reveals a behavioural reweighting of information cues as product condition declines, indicating that buyers become more risk-averse and utility-driven in lower-quality segments.

Moreover, this differentiation underscores the importance of moving beyond generic models that assume homogeneous buyer behaviour across product types. By empirically demonstrating that signal responsiveness is moderated by product condition, the study provides a more accurate representation of buyer decision-making under quality uncertainty—an area under-theorised in both remanufacturing and auction literature.

The application of SHAP-based XAI methods provides transparency into how and why signal effectiveness varies across product condition levels. It shows that signal interactions are not merely additive or linear but instead shift in magnitude and direction depending on the underlying product condition. This nuance extends the explanatory power of auction models and reflects how buyers dynamically reassess information cues in light of perceived product quality. Furthermore, the study identifies practical signal thresholds (e.g., tipping points in

image count or bid volume) that are condition-specific, offering direct implications for adaptive listing strategies.

This study makes the third contribution to the literature on online auctions and bidder heterogeneity by focusing on a domain that has been largely overlooked—bidding behaviour in auctions for remanufactured products. While extensive prior work has examined pricing mechanisms, WTP, and market signals in the context of remanufactured goods, and a separate body of research has explored bidder heterogeneity in online auctions (Bapna *et al.*, 2004; Goes, Karuga and Tripathi, 2012; Mancha *et al.*, 2014; Cui *et al.*, 2020), no prior study has empirically investigated bidder heterogeneity specific to remanufactured goods. This represents a critical gap in both streams of literature—a gap this study fills by offering the first behavioural classification of bidders in the online auction market for remanufactured iPhones.

This research extends the seminal framework introduced by Bapna *et al.* (2004) by including two additional behavioural dimensions—Feedback Score (*FEED*) and Average Bid Increment (*ABINC*)—in conjunction with the original three variables: Number of Bids (*NOB*), Time of Entry (*TOE*), and Time of Exit (*TOX*). This expanded feature space allows for a more comprehensive behavioural segmentation of bidders. Notably, the integration of *ABINC* captures bidder aggressiveness, while *FEED* reflects bidder reputation and platform familiarity—dimensions that are particularly relevant in high-information-asymmetry environments such as remanufactured product markets yet underexplored in prior clustering-based research.

Furthermore, the study introduces a new behavioural type—Shooters, positioned between Snipers and Participators in terms of strategic intensity and auction engagement. This emergent bidder profile, uncovered through unsupervised K-means clustering and subsequently validated through SHAP-enhanced classification, challenges the conventional typologies and offers fresh insight into how intermediate strategies manifest in auction environments. Unlike Snipers, who operate with high efficiency through last-minute entry, or Participators, who engage continuously but inefficiently, Shooters display mid-to-late entry, high bid frequency, and elevated bid increments. Despite having lower feedback scores than Snipers, Shooters demonstrated a strong win rate (41.6%) and moderate efficiency, suggesting that hybrid strategies can outperform more naive or undisciplined bidding behaviours.

Overall, these studies underscore the complexity of bidder behaviours in online auctions, shaped by personal motivations, strategies, and auction design factors. Using clustering to identify bidder types has shown potential in refining auction design, promoting broader participation, and maximising revenue. This study addresses this research gap by categorising bidder behaviours in remanufactured product auctions, identifying heterogeneity in bidder characteristics and strategies. By integrating clustering with SHAP, it overcomes interpretability limitations and provides clear insights into the key drivers of each bidder type. In addition to advancing auction theory, this research contributes to operational research by offering a transparent and data-driven framework for behavioural segmentation under uncertainty. It also informs closed-loop supply chain studies by shedding light on secondary market dynamics and how buyer behaviour varies by product condition, supporting more effective remarketing strategies for remanufactured goods.

7.5 Limitations of the Study and Future Directions

Despite offering valuable insights into the auction dynamics of remanufactured products, this study is subject to several limitations. These limitations provide meaningful avenues for future research aimed at deepening and broadening the understanding of this market.

1) Incomplete Representation of Market Signals

Although the study incorporates a wide range of market signals, such as seller feedback scores, number of bids, starting prices, product condition, number of images, historical sales and auction competitiveness, it excludes several potentially influential features. For instance, the availability of original (non-stock) product photos, the number of watchers (users tracking an auction), the total number of items previously sold by a seller, and the textual content of buyer feedback were not included due to data constraints. These additional signals may provide more granular insights into buyer trust, listing quality, and perceived value, especially in contexts of high information asymmetry like remanufactured products. Future studies should aim to incorporate these omitted variables for a more complete modelling of buyer decision-making and auction outcomes.

2) Partial Coverage of Product Condition Categories

A second limitation lies in the limited range of remanufactured product conditions analysed. This study included only three classifications—Excellent, Very Good, and Good—while excluding Certified Refurbished and Seller-Refurbished, both of which are common and carry distinctive signalling implications. This exclusion was mainly due to data imbalances, which limited the feasibility of rigorous analysis across all categories. However, these omitted condition labels may significantly influence consumer perception and WTP. Future research

should strive to collect balanced samples across all remanufactured condition tiers to more fully capture the spectrum of quality signals influencing auction dynamics.

3) Generalisability of Bidder Behaviour Across Product Categories

The analysis of bidder heterogeneity was conducted using auction data for remanufactured iPhones. Although smartphones are a representative category within consumer electronics, the findings may not be generalisable to other remanufactured product types such as laptops, appliances or power tools. Consumer valuation, perceived risk, and decision-making heuristics are likely to vary across product categories. Consequently, the bidder segments identified in this study may not fully reflect broader behavioural trends. Future studies should replicate this analysis across diverse remanufactured goods to evaluate the consistency of bidding behaviours and segment structures.

4) Dataset Limitations

A notable constraint of this study is the relatively limited volume of data, especially considering the requirements of robust ML and segmentation analysis. While the bidder heterogeneity analysis (Chapter 6) utilised 13,468 bidder-level records from 986 auctions, the first study (Chapter 4) used only 939 auction-level data points, and the second (Chapter 5) involved approximately 1,004 records, which became further fragmented when disaggregated by product condition. Compared to fixed-price transactions, auction-based listings, particularly for remanufactured goods, are relatively rare. This scarcity of auction data imposes constraints on generalisability, robustness, and the granularity of subgroup analysis. Future research would benefit from assembling larger and more balanced datasets, ideally including longitudinal elements to explore trends over time. Additionally, incorporating complementary behavioural

data (e.g., browsing patterns, click-through rates, and user interaction histories) could enrich the analysis and improve interpretive power.

5) Methodological Constraints

While ML methods demonstrate strong predictive capabilities and effectively capture complex non-linear relationships, they are inherently limited in interpretability and primarily yield correlational insights. To address this limitation, the present study incorporates XAI techniques, specifically SHAP, to enhance model transparency and interpretability. However, such methods do not establish causal relationships; they merely identify which features are influential in prediction, without explaining the underlying reasons for these associations. To advance from descriptive and predictive analysis toward explanatory depth, future research should adopt causal inference approaches, such as propensity score matching, instrumental variable techniques or structural equation modelling, to uncover the mechanisms driving consumer behaviour in auction contexts.

6) Platform-Specific Scope

This study focuses exclusively on auction transactions conducted via eBay. While eBay represents a major global platform for remanufactured goods, it has unique auction mechanics, seller tools, and user demographics that may not be representative of other online marketplaces. Consumer behaviour, trust mechanisms, and competitive dynamics could vary considerably on platforms such as Amazon Renewed, Back Market or region-specific platforms. Therefore, future research should expand the platform scope to assess whether the identified relationships and behavioural patterns hold in other digital environments. Cross-platform comparative analysis would also allow researchers to distinguish between un

Taken together, these limitations do not diminish the contributions of this study but rather highlight critical areas for further exploration. By identifying gaps in signal representation, product condition granularity, platform generalisability, and methodological scope, this research establishes a foundation for more comprehensive and context-aware investigations into remanufactured product markets. Future studies that integrate a wider array of behavioural signals, larger and more diverse datasets, and causal inference techniques—across various platforms and product categories—will be well-positioned to deepen theoretical understanding and deliver more actionable insights for practitioners. As remanufactured goods continue to play an increasingly vital role in circular economy models, enhancing the rigour and relevance of auction-based market analysis remains both a timely and impactful research agenda.

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Appendix

This appendix provides supplementary information that is not discussed in detail within the main text. It primarily includes tables and supporting data relevant to the specific procedures outlined in the core chapters.

Table A.1: Comparison of Train-Test Split Ratios in Study 1 (random_state=23)

Ratio	Metrics	Random Forest		XGBoost	
		Test	Cross-validate	Test	Cross-validate
8:2	R2	0.7189	0.6727	0.7205	0.6565
	MAE	0.1267	0.1287	0.1263	0.1317
	RMSE	0.0806	0.0872	0.0812	0.0893
7:3	R2	0.7051	0.6780	0.6748	0.6621
	MAE	0.1248	0.1287	0.1311	0.1315
	RMSE	0.0824	0.0886	0.0861	0.0908
6:4	R2	0.7081	0.6573	0.6667	0.6455
	MAE	0.1219	0.134	0.1303	0.1361
	RMSE	0.0841	0.0932	0.0867	0.0934

Table A.2: Comparison of Train-Test Split Ratios in Study 1 (random_state=11)

Ratio	Metrics	Random Forest		XGBoost	
		Test	Cross-validate	Test	Cross-validate
8:2	R2	0.7102	0.6748	0.6834	0.6649
	MAE	0.1201	0.1304	0.1255	0.1318
	RMSE	0.0821	0.0903	0.0861	0.0884
7:3	R2	0.6792	0.6734	0.6660	0.6510
	MAE	0.1239	0.1324	0.1265	0.1367
	RMSE	0.0829	0.0903	0.0817	0.0933
6:4	R2	0.6414	0.6718	0.6256	0.6186
	MAE	0.1372	0.1299	0.1402	0.1397
	RMSE	0.0897	0.0903	0.0961	0.0961

Table A.3: Comparison of Train-Test Split Ratios in Study 2

Ratio	Metrics	Random Forest		XGBoost	
		Test	Cross-validate	Test	Cross-validate
8:2	R2	0.8364	0.8292	0.8603	0.8297
	MAE	0.0647	0.0651	0.0598	0.0647
	RMSE	0.0446	0.0458	0.0428	0.0459
7:3	R2	0.8142	0.8232	0.8426	0.8248

6:4	MAE	0.0710	0.0655	0.0653	0.0655
	RMSE	0.0474	0.0474	0.0451	0.0477
	R2	0.7976	0.8248	0.8073	0.8247
	MAE	0.0716	0.0659	0.0698	0.0656
	RMSE	0.0473	0.0486	0.0492	0.0482

Table A.4: Results of Alternative Clustering Method: DBSCAN

Rsank	Parameters		Result	Evaluation
	eps	min_samples	n_clusters	silhouette score
1	0.55	20	4	0.451858
2	1.35	7	2	0.422431
3	1.25	3	2	0.422431
4	1.3	1	2	0.422431
5	1.3	2	2	0.422431

Table A.5: Comparison of Train-Test Split Ratios in Study 3

Ratio	Metrics	XGBoost
8:2	Test Accuracy	0.9933
	Test Precision	0.9934
	Test Recall	0.9928
	Test F1 Score	0.9931
	Cross-validate Accuracy	0.9960
	Cross-validate Precision	0.9960
	Cross-validate Recall	0.9959
	Cross-validate F1 Score	0.9959
7:3	Test Accuracy	0.9946
	Test Precision	0.9946
	Test Recall	0.9944
	Test F1 Score	0.9945
	Cross-validate Accuracy	0.9949
	Cross-validate Precision	0.9950
	Cross-validate Recall	0.9948
	Cross-validate F1 Score	0.9949
6:4	Test Accuracy	0.9954
	Test Precision	0.9954
	Test Recall	0.9954
	Test F1 Score	0.9954
	Cross-validate Accuracy	0.9946
	Cross-validate Precision	0.9946
	Cross-validate Recall	0.9944
	Cross-validate F1 Score	0.9945