Predicting Consumer Preferences for Furniture Products on E-commerce Platforms: An Analysis Using Machine Learning and Favorite Listing Data

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The rapid growth of e-commerce platforms presents unique opportunities to analyze consumer behavior and predict product preferences in the furniture industry. This study explores the use of machine learning techniques to predict consumer choices for furniture products based on favorite listing data from e-commerce platforms. A dataset of 239 furniture products was collected, categorized into three groups: most preferred, moderately preferred, and least preferred. Key attributes, including furniture type, dimensions (width, depth, height), color, material, and price, were analyzed. Machine learning models, specifically Decision Trees and Random Forests, were applied to develop prediction models for these categories. The models were assessed using metrics such as accuracy, precision, sensitivity, and F1-score. Results indicated that the Random Forest model outperformed the Decision Tree, achieving 83% accuracy in predicting preference categories. Feature importance analysis highlighted that price and physical dimensions were the most significant factors influencing consumer preferences. These findings suggest that practical and economic aspects are prioritized over aesthetic features when choosing furniture. The study demonstrates the potential of machine learning in predicting consumer behavior, offering valuable insights for manufacturers and retailers in optimizing product development, inventory management, and marketing strategies.

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INTRODUCTION

The growing influence of the Internet on modern life has led to a significant increase in online shopping. The large amounts of data collected on e-commerce platforms enable management to make informed decisions and gain deeper insights into consumer behavior. In addition, these forecasts enable more accurate financial budgeting, more effective operational planning, and more efficient inventory policies (Sun *et al*. 2008). Artificial intelligence (AI) has become an essential element of Industry 4.0 and is expected to maintain its importance with the advent of Industry 5.0. At the same time, companies are increasingly integrating AI technologies into all operational areas. This phenomenon reflects the profound impact of AI on industrial processes and business models (Sigov *et al*. 2022; de Waal *et al*. 2024). Machine learning (ML) algorithms have emerged as a

powerful tool for solving complex industry-specific forecasting problems. However, research studies in the furniture industry are still limited. This study fills this gap by uniquely applying ML techniques to big data from e-commerce platforms, focusing on predicting consumer preferences in the furniture sector based explicitly on favorite listing behavior. This approach makes a unique contribution to the field, as it combines the power of ML with rich data obtained from online shopping platforms. Applying ML techniques makes it possible to analyze large amounts of data, identify patterns, and formulate predictions. The use of ML algorithms facilitates the acceleration of innovation by processing large data sets and running simulations (Xue *et al*. 2024).

Random forest (RT) is a widely used supervised ML algorithm. This algorithm can be effectively applied to classification and regression problems. Random forest has gained popularity among researchers and practitioners due to its adaptability to different data sets and high accuracy (Breiman 2001; Lee *et al*. 2024). Decision tree (DT) is a nonparametric supervised learning technique for classification or regression. It simplifies and visualizes complex decision processes by modeling patterns in the data set in a hierarchical structure. The DT works by repeatedly partitioning the data according to specific characteristics and making the most appropriate distinction at each node. This way, effective results can be achieved in classification and regression problems (Song and Ying 2015; Alakbari *et al*. 2023).

Over the past decade, e-commerce platforms such as Amazon and Alibaba have become indispensable tools for consumers searching for and purchasing products. The success of these platforms can be attributed to their sophisticated ability to collect and analyze consumer behavior data. E-commerce sites use recommendation systems to provide personalized product recommendations to individual users, thereby encouraging consumers to discover and purchase products that match their established shopping habits. This approach has the dual benefit of improving the user experience and increasing sales (Zhang *et al*. 2020; Zhou *et al*. 2024). In recent years, there has been a significant increase in research into using ML techniques to predict consumer behavior and future buying trends. These approaches use a variety of algorithms, such as logistic regression, decision trees, artificial neural networks, and support vector machines, to identify patterns in consumer data. The identified patterns are then used to create models that predict consumer preferences (Moro *et al*. 2014; Liu *et al*. 2024). To illustrate, the deep learning approach proposed by Gabel and Timoshenko (2022) extracts preference representations based on customers' purchase history and uses this information to predict future product choices.

The furniture industry has complex variables that must be considered when predicting consumer preferences and behavior. Consumers' furniture choices are influenced not only by the tangible characteristics of the products in question (*e.g.*, dimensions, composition, color) but also by individual aesthetic tendencies and economic conditions. This requires using more sophisticated and accurate analytical tools to accurately predict the number of times furniture products will be added to the favorites list. Applying ML algorithms to extract meaningful insights from large data sets is a promising way to improve such predictions' accuracy by overcoming traditional methods' limitations.

In this study, the aim was to predict consumers' preferences for furniture products using data from e-commerce platforms and ML algorithms. Furniture products were classified into three groups based on the number of times they had been added to the favorites list: highly preferred, moderately preferred, and low preferred. This approach is a unique contribution to the field, combining the power of ML with rich data from online shopping platforms.

The study used two major ML algorithms: Decision Trees and Random Forests. These algorithms were chosen based on their proven effectiveness in handling complex, multidimensional data and their ability to provide interpretable results. The study used a comprehensive dataset of 239 furniture products, including variables such as furniture type, dimensions (width, depth, height), color, primary material, and price. Predictive models were built and evaluated using standard classification metrics such as accuracy, precision, sensitivity, and F1 score. In addition, feature importance analysis was performed to determine the relative impact of different factors on consumer preferences. The results of this research have important practical implications for the furniture industry and could transform production planning, inventory management, and marketing strategies. By accurately predicting consumer preferences based on the number of times they are added to a favorites list, companies can optimize their operations, reduce waste, and better meet customer demands.

EXPERIMENTAL

Methodology

Data collection and pre-processing

This study utilized a comprehensive dataset of 239 furniture products, meticulously collected from several publicly accessible Turkish e-commerce platforms. Data included furniture type, dimensions, color, material, price, and preference category counts. The data were collected between December 11, 2022, and August 11, 2023.

The collected data underwent standard cleaning, missing value handling, and outlier correction. Table 1 shows Sample Furniture Product Data (excerpt).

Table 1. Sample Furniture Product Data (excerpt)

Furniture Type	Width (cm)	Depth (cm)	Height (cm)	Color	Main Material	Price (TL)	Favorite Count
TV Unit	120	35	61	Dark	Particle Board (PB)	459	60568
TV Unit	150	30	44	Light	Particle Board (PB)	838	60072
TV Unit	120	30	40	Light	Particle Board (PB)	529	58101
Coffee Table	34	18	49	Dark	Particle Board (PB)	289	56247

Data Categorization Using K-means Clustering

The K-means clustering algorithm was used to more objectively categorize furniture items based on the number of times they were added to the favorites list. K- means clustering was chosen because of its effectiveness in identifying natural groups in the data. Furniture items were categorized into three groups based on the number of times they were added to the favorites list: most preferred, moderately preferred, and least preferred. To address the recommendation for specific classification criteria, the K-means algorithm identified the following ranges for each category based on the 'number of times added to favorites list' attribute:

Least Preferred: 0 – 15231 favorite listings
Moderately Preferred: 15232 – 33193 favorite listings
Most Preferred: 33194 – 60568 favorite listings

These ranges were determined by the clustering process, which aimed to minimize the within-cluster variance and maximize the between-cluster variance, thereby creating distinct and meaningful groups. The 'k' parameter for the K-means algorithm was set to 3, as the aim was to categorize the furniture into three preference levels as per the study's objective. This categorization was used as the target variable for the prediction models used in this study.

Model Building

In this study, consumer preferences for furniture products operated as the frequency with which items are added to users' favorites—using Decision Trees (DT) and Random Forest (RF). These algorithms were selected due to their ability to handle mixed-type, multidimensional data and capture non-linear relationships while retaining interpretability for industry stakeholders. DT provides transparent, rule-based structures that clarify how attributes drive classification, whereas RF—an ensemble that aggregates the predictions of multiple decision trees—improves accuracy and mitigates overfitting relative to a single tree, yielding robust generalization on complex e-commerce data (Breiman 2001). Prior work further supports the use of DT/RF in e-commerce analytics and preference prediction (Haque 2024; Mustakim *et al.* 2024). Both models were trained on the collected e-commerce dataset containing categorical (*e.g.*, type, color, primary material) and numerical (*e.g.*, width, depth, height, price) features; the evaluation procedure and performance metrics are detailed in the following subsection. The dataset was divided into training and test sets, with 70% allocated for training and the remaining 30% for testing. This 70/30 split is a widely adopted standard in ML, balancing the need for sufficient training data to build robust models and enough testing data to evaluate model performance effectively (Pham *et al.* 2019). Such a division helps in mitigating overfitting and provides a reliable assessment of the model's generalization capabilities.

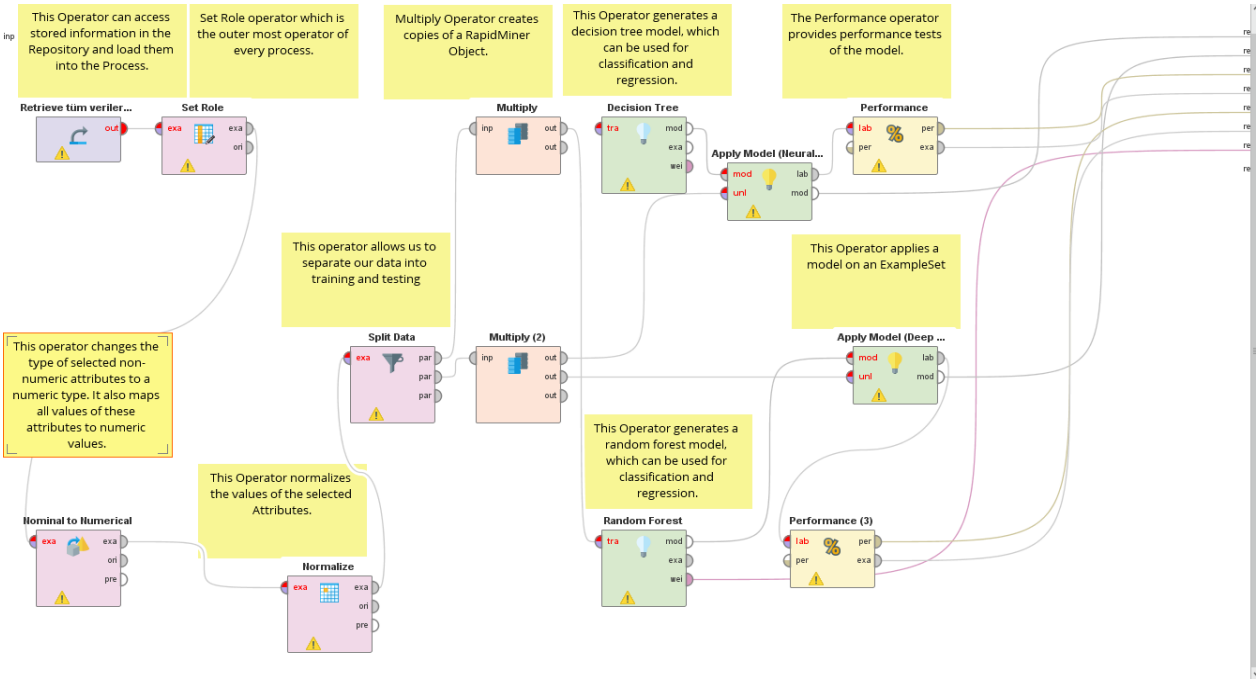

Fig. 1. RapidMiner process (software interface screenshot) used to train and evaluate the models

In the context of furniture preference modeling, this approach aligns with methodologies employed in recent studies, such as Yu *et al*. (2023), who utilized a similar data partitioning strategy to analyze the relationship between consumer personality traits and preferences for wood furniture product characteristics. The models in this study were trained and evaluated using RapidMiner, a software platform widely recognized for its applicability in scientific research and ML tasks (Gonçalves *et al*. 2013; Mozaffarinya *et al*. 2019; Gonçalves *et al*. 2020; Sher *et al*. 2022). The process created for applying the models in the RapidMiner program is given in Fig. 1. RapidMiner process (software interface screenshot) was used to train and evaluate the models.

To optimize model performance, comprehensive hyperparameter tuning was conducted using grid search methodology through RapidMiner's Optimize Parameters (Grid) operator. This operator systematically executed the subprocess for all combinations of selected parameter values to identify the optimal configuration that maximized prediction accuracy. Table 2 presents the three most critical hyperparameters for both Random Forest and Decision Tree models, along with their optimal values determined through this grid search process.

Table 2. Most Important Hyperparameters for Random Forest and Decision Tree Models

Algorithm	Parameter	Optimal Value	Definition
Random Forest	number_of_trees	21	The number of decision trees in the ensemble
Random Forest	maximal_depth	0 (unlimited)	Maximum depth allowed for each tree in the forest
Random Forest	use_local_random_seed	true	Use a local random seed for reproducible results within this operator.
Decision Tree	maximal_depth	70	Maximum depth of the single decision tree
Decision Tree	minimal_leaf_size	1	Minimum number of examples required in a leaf node.
Decision Tree	apply_pruning	false	Whether to apply post-pruning to the tree

Model Evaluation

The model's performance was comprehensively evaluated using accuracy, precision, and sensitivity, which are standard metrics for classification tasks in machine learning, providing a robust assessment of overall correctness, positive prediction reliability, and true positive identification, respectively (Sokolova and Lapalme 2009; Puri *et al*. 2017; Siering *et al*. 2018; Szabó *et al*. 2024).

Accuracy was calculated by dividing the total number of correctly classified observations by the total number of observations:

$$\text{"Accuracy"} = (\text{"TP"} + \text{"TN"}) / (\text{"TP"} + \text{"FP"} + \text{"TN"} + \text{"FN"}) \quad (1)$$

Precision is a metric that measures the accuracy of a classifier, *i.e.*, whether a sample classified as belonging to a certain class belongs to that class:

$$\text{"Precision"} = \text{"TP"} / (\text{"TP"} + \text{"FP"}) \quad (2)$$

Sensitivity is defined as the ratio of true positive predictions to the number of positive samples:

"Sensitivity" = "TP" / ("TP" + "FN") (3)

In Eq. 3, TP is True Positive; TN means True Negative; FP is False Positive; and FN denotes False Negative.

These metrics were used to compare the performances of different algorithms and permit them to select the best-performing model.

Feature Importance Analysis

Following the identification of the Random Forest model as the most robust predictor, a comprehensive feature importance analysis was conducted to quantify the influence of each attribute on consumer preferences for furniture products. This analysis was performed using the 'Attribute Weights' functionality inherent to the Random Forest operator in RapidMiner. The calculation of these weights is based on the principle of measuring the total reduction in node impurity (specifically, the Gini impurity criterion) that an attribute provides across all decision trees within the ensemble. For each attribute, its importance score is computed as the sum of the Gini impurity decreases for every node where that attribute was utilized for splitting the data. Consequently, attributes that are frequently selected for splitting and contribute significantly to the homogeneity of child nodes receive higher importance weights. This quantitative approach made it possible to objectively rank the factors influencing consumer choices, revealing the relative impact of attributes such as price, dimensions, and material on product favoritism. This detailed methodology ensures that the findings regarding feature importance are transparent and can be independently verified or applied by other researchers interested in similar analytical approaches.

After selecting the best-performing model (Random Forest; accuracy = 83.10%), the next step was to compute the global feature importance in RapidMiner using the Weight by Tree Importance operator. This method returns an ExampleSet with attributes and normalized weights (sum = 1). Each weight equals the total decrease in node impurity contributed by that attribute across all splits in the forest, weighted by the number of samples at each node; improvements are computed with the same splitting criterion as the model (Gini for classification). Only the following features were evaluated: Price, Width, Height, Depth, Color, Primary Material, and Furniture Type.

RESULTS AND DISCUSSION

This section reports the empirical findings and their implications. Using Random Forest (RF) and Decision Tree (DT), there was an evaluation of the predictive performance with accuracy, precision, sensitivity (recall), and F1-score. As summarized in Table 2, RF consistently outperformed DT: 83.10% overall accuracy for RF *versus* 73.24% for DT. Class-level F1-scores likewise favored RF (Class 0: 71.43%; Class 1: 70.59%; Class 2: 89.36%) over DT (Class 0: 53.33%; Class 1: 48.28%; Class 2: 83.67%), indicating better generalization across "most," "moderately," and "least" preferred categories. These gains are consistent with RF's ensemble learning, which reduces overfitting relative to a single tree and captures non-linear interactions in mixed-type e-commerce data.

Following model assessment, a feature-importance analysis with the best-performing RF model showed that Price (0.304) and dimensional attributes—Width (0.228), Height (0.188), Depth (0.146)—were the dominant drivers of preference, whereas Color (0.073), Primary Material (0.036), and Furniture Type (0.025) were comparatively less influential. Practically, this implies that consumers prioritize economic and spatial constraints over aesthetic or categorical attributes when selecting furniture online; pricing and size-fit thus emerge as primary levers for product, inventory, and merchandising decisions.

Model Performance Comparison

Table 3 presents a detailed comparison of the performance metrics for both the RF and DT models when applied to the e-commerce dataset.

Table 3. RF *vs*. DT Performance on the E-commerce Dataset

Model	Class	Precision	Recall	F1-Score	Accuracy
Random Forest	0	83.33%	62.50%	71.43%	83.10%
	1	70.59%	70.59%	70.59%	
	2	87.50%	91.30%	89.36%	
Decision Tree	0	57.14%	50.00%	53.33%	73.24%
	1	58.33%	41.18%	48.28%	
	2	78.85%	89.13%	83.67%	

Note: 0 = Most preferred furniture, 1 = Moderately preferred furniture, 2 = Least preferred furniture

The Random Forest Confusion Matrix (Table 4) and Decision Tree Confusion Matrix (Table 5) demonstrate the detailed performance breakdown.

Table 4. Random Forest Confusion Matrix

	True Most Preferred	True Moderately Preferred	True Least Preferred	Class Precision
Pred. Most Preferred	5	1	0	83.33%
Pred. Moderately Preferred	1	12	4	70.59%
Pred. Least Preferred	2	4	42	87.50%
Class Recall	62.50%	70.59%	91.30%	

Table 5. Decision Tree Confusion Matrix

	True Most Preferred	True Moderately Preferred	True Least Preferred	Class Precision
Pred. Most Preferred	4	1	2	57.14%
Pred. Moderately Preferred	2	7	3	58.33%
Pred. Least Preferred	2	9	41	78.85%
Class Recall	50.00%	41.18%	89.13%	

The RF model demonstrated superior overall performance with an accuracy rate of 83.10%, surpassing the DT model's accuracy of 73.24%. This suggests that the RF algorithm more effectively captures complex patterns in e-commerce furniture preference data, consistent with recent findings showing the superior predictive capabilities of RF over DT (Helmud *et al*. 2024). In terms of model strengths and weaknesses, the RF model exhibited consistent performance across all preference categories and demonstrated high accuracy, particularly in identifying the least preferred furniture products. This consistency is attributed to RF's ensemble learning approach, which mitigates overfitting and enhances generalization by aggregating predictions from multiple decision trees (Kinasih *et al*. 2025).

Conversely, the DT model showed solid performance in determining the least preferred products, while exhibiting lower overall accuracy. However, it encountered difficulties in distinguishing between the most and moderately preferred products.

The RF algorithm implemented in this study showcased remarkable success, meeting the performance criteria widely accepted in the literature (Sokolova and Lapalme 2009; Zhu *et al*. 2010; Luo *et al*. 2016). Its ability to handle high-dimensional data and provide robust predictions aligns with findings from other recent studies where RF models outperformed even more complex algorithms such as deep learning models in specific contexts, such as predicting furniture prices (Bardak 2023).

Feature Importance

In this study, the most powerful RF algorithm was used to determine the importance levels of the features that influence the number of favorites of furniture products. The factors analyzed included different characteristics such as height, width, depth, color, primary material, price, and type of furniture. Table 6 shows in detail the important weights of these factors obtained from the e-commerce platforms data using the RF algorithm. These results contribute significantly to a more comprehensive understanding of the factors that shape consumer preferences in the furniture sector and can provide valuable insights to stakeholders in the sector.

Table 6. Weights of Factors Based on Furniture Data Obtained through the Random Forest Algorithm

Factor	Importance Weight
Price (TL)	0.304
Furniture Width	0.228
Furniture Height	0.188
Furniture Depth	0.146
Furniture Color	0.073
Furniture Primary Material	0.036
Furniture Type	0.025

The RF algorithm's analysis of furniture attributes reveals significant insights into consumer preferences in the furniture industry. Price emerges as the dominant factor with the highest importance weight (0.304), indicating strong consumer price sensitivity. This is closely followed by dimensional attributes - width, height, and depth - suggesting that the physical size of furniture plays a critical role in purchase decisions, likely due to space constraints or aesthetic considerations. Color is moderately important, while furniture

material and type are relatively unimportant. This hierarchy of factors suggests that consumers prioritize practical and economic aspects over aesthetic or categorical features when selecting furniture.

This finding aligns with previous research, where price was found to be a decisive factor in furniture purchasing decisions and RF models demonstrated high accuracy in predicting furniture prices (Bardak 2023). Dimensional attributes particularly width, height, and depth also significantly impact consumer decisions. Gudarzi *et al*. (2022) similarly found that physical dimensions of furniture are critical considerations for consumers, often outweighing other product characteristics in importance.

While color holds moderate importance, material and type appear to be less influential factors. Supporting this, Guzel (2020) reported that consumers in Kayseri, Turkey, frequently prioritize affordable and functional composite furniture over more expensive solid wood alternatives. Moreover, Yu *et al*. (2023) highlighted that consumer personality traits such as extraversion and conscientiousness significantly influence the perceived importance of product features like quality and design, although these factors still ranked below economic and dimensional considerations.

This hierarchy of factors suggests that for the furniture products analyzed in this study (coffee tables and TV units), practical and economic aspects such as price and physical dimensions are significant factors influencing consumer preferences. While these findings highlight the importance of practical and economic factors within our specific dataset, it is important to acknowledge that consumer preferences for furniture can be highly nuanced and influenced by various other factors, including aesthetic considerations, specific furniture categories (*e.g*., functional *vs*. decorative), and diverse user demographics (*e.g*., young people, parents). Future research could explore these aspects in more detail by examining a broader range of furniture categories and demographic segments.

CONCLUSIONS

The aim of this study was to contribute to the existing literature on the application of machine learning in consumer behavior analysis, with a particular focus on the furniture industry.

1. This study examined the potential of machine learning algorithms in predicting consumer preferences for furniture products using e-commerce favoriting data. The research aimed to estimate the number of favorites of furniture products using the capabilities of Decision Trees and Random Forest algorithms. The analysis demonstrated that the RF algorithm exhibited superior performance (accuracy of 83.10%) compared to the DT model (73.24% accuracy).
2. Feature importance analysis using the RF model revealed that price and the physical dimensions of the furniture (width, height and depth) significantly influenced consumer preferences. These findings highlight the importance of practical considerations, such as space and financial constraints, in e-commerce furniture preference decisions. In contrast, factors such as furniture type and material were found to have a relatively limited influence on consumer choice. This suggests that aesthetic or categorical features may be secondary to functional attributes.

3. These findings may provide valuable insights for furniture manufacturers and retailers, enabling them to optimize product development, inventory management, and marketing strategies based on predictive analysis.
4. The successful application of machine learning techniques in this study demonstrates their potential to contribute to decision-making processes in the furniture industry. As e-commerce platforms continue to generate large amounts of consumer data, the integration of advanced analytics will be critical to driving business success and responding to changing market trends.

It should be noted that the present findings are specific to the functional furniture categories examined (coffee tables and TV units) and may not be generalizable to decorative furniture items or different consumer demographic groups. Future studies should investigate how preferences vary across different furniture categories and user segments to provide a more comprehensive understanding of consumer behavior in the furniture industry.

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APPENDIX: Data Table

Furniture Type	Furniture Width (cm)	Furniture Depth (cm)	Furniture Height (cm)	Furniture Color	Main Material	Price (TL)	Number of Favorites
TV Unit	120.00	35.00	61.00	Dark color	Particleboard (PB)	459.00	60568
TV Unit	150.00	29.50	44.10	Light color	Particleboard (PB)	838.00	60072
TV Unit	120.00	30.00	40.00	Light color	Particleboard (PB)	529.00	58101
Coffee Table	34.00	18.00	49.00	Dark color	Particleboard (PB)	289.50	56247
Coffee Table	34.00	34.00	49.00	Dark color	Particleboard (PB)	289.00	56244
Coffee Table	60.00	44.00	46.00	Light color	Particleboard (PB)	529.00	55310
TV Unit	180.00	40.00	45.00	Dark color	Particleboard (PB)	2049.00	54332
TV Unit	180.00	40.00	45.00	Dark color	Particleboard (PB)	1844.00	53944
TV Unit	160.00	25.50	49.00	Dark color	Particleboard (PB)	900.00	47737
TV Unit	160.00	25.50	49.00	Light color	Particleboard (PB)	899.00	47610
TV Unit	120.00	30.00	40.00	Dark color	Particleboard (PB)	529.00	45772
TV Unit	180.00	35.00	48.60	Dark color	Particleboard (PB)	2309.00	44882
TV Unit	120.00	46.00	43.00	Dark color	Particleboard (PB)	449.00	44225
TV Unit	180.00	35.00	49.00	Dark color	Particleboard (PB)	1965.00	44136
TV Unit	180.00	29.60	45.00	Dark color	Particleboard (PB)	989.00	43120
TV Unit	180.00	35.00	54.00	Dark color	Particleboard (PB)	1429.00	43114
TV Unit	180.00	35.00	54.00	Dark color	Particleboard (PB)	1429.00	43095
TV Unit	180.00	29.60	45.00	Dark color	Particleboard (PB)	990.00	42955
TV Unit	180.00	29.60	44.30	Dark color	Particleboard (PB)	1750.00	40169
Coffee Table	60.00	44.00	46.00	Light color	Particleboard (PB)	529.00	39887
TV Unit	150.00	30.00	35.00	Light color	Particleboard (PB)	1240.00	39505
TV Unit	150.00	30.00	35.00	Light color	Particleboard (PB)	1239.00	39179
TV Unit	180.00	29.60	44.30	Dark color	Particleboard (PB)	1540.00	38606
Coffee Table	33.00	33.00	46.00	Light color	Particleboard (PB)	310.00	38283
Coffee Table	45.00	35.00	40.00	Dark color	MDF + PB	289.00	38106
Coffee Table	34.00	18.00	49.00	Dark color	Medium-density FB	289.00	37230
TV Unit	160.00	30.00	49.00	Dark color	Particleboard (PB)	1050.00	36369
TV Unit	160.00	30.00	49.00	Light color	Particleboard (PB)	1079.00	36037
TV Unit	180.00	35.00	45.00	Light color	Particleboard (PB)	1294.00	33193
TV Unit	184.00	183.00	30.00	Dark color	Particleboard (PB)	1900.00	32916
TV Unit	180.00	35.00	135.00	Light color	Particleboard (PB)	1295.00	32592
TV Unit	120.00	30.00	40.00	Dark color	Particleboard (PB)	560.00	32550
TV Unit	180.00	32.00	30.00	Light color	Particleboard (PB)	954.00	32550
Coffee Table	33.50	33.50	46.00	Light color	Particleboard (PB)	310.00	32030
TV Unit	180.00	30.00	32.00	Light color	Particleboard (PB)	702.00	31954
Coffee Table	40.00	35.00	45.00	Light color	Medium-density FB	289.00	31797
Coffee Table	60.00	37.00	46.00	Light color	Medium-density FB	529.00	30109
Coffee Table	37.00	18.00	51.00	Light color	Medium-density FB	588.00	29676
Coffee Table	33.00	33.00	52.00	Light color	Medium-density FB	349.00	29627
TV Unit	138.00	15.00	45.00	Dark color	Particleboard (PB)	957.00	29539
TV Unit	138.00	15.00	45.00	Dark color	Particleboard (PB)	956.00	29446

TV Unit	120.00	30.00	42.00	Light color	Particleboard (PB)	619.00	28064
TV Unit	180.00	35.00	54.00	Dark color	Particleboard (PB)	2069.00	27824
TV Unit	120.00	30.00	42.00	Light color	Particleboard (PB)	610.00	27633
TV Unit	180.00	54.00	54.00	Dark color	Particleboard (PB)	2070.00	27544
Coffee Table	33.00	18.00	50.00	Light color	Particleboard (PB)	289.00	25005
TV Unit	150.00	31.40	44.40	Light color	Particleboard (PB)	945.00	24330
TV Unit	150.00	31.40	44.40	Light color	Particleboard (PB)	950.00	24228
TV Unit	150.00	31.40	44.40	Light color	Particleboard (PB)	1050.00	24110
TV Unit	138.00	29.50	42.60	Dark color	Particleboard (PB)	740.00	23350
TV Unit	180.00	35.00	45.00	Light color	Particleboard (PB)	1294.00	23201
TV Unit	140.00	33.00	40.00	Light color	Particleboard (PB)	670.00	22560
TV Unit	140.00	33.00	40.00	Light color	Particleboard (PB)	669.00	22412
TV Unit	180.00	35.00	48.30	Light color	Particleboard (PB)	1362.00	22294
TV Unit	180.00	35.00	48.00	Light color	Particleboard (PB)	1143.00	22074
TV Unit	180.00	35.00	48.30	Dark color	Particleboard (PB)	2127.00	21141
Coffee Table	34.00	34.00	49.00	Light color	Medium-density FB	289.00	21048
TV Unit	138.00	35.00	50.00	Dark color	Particleboard (PB)	900.00	21040
TV Unit	150.00	30.00	44.00	Light color	Particleboard (PB)	1100.00	20965
TV Unit	150.00	30.00	43.00	Light color	Particleboard (PB)	1100.00	20777
Coffee Table	54.00	40.00	75.00	Dark color	MDF + PB	791.00	20754
Coffee Table	54.00	40.00	75.00	Dark color	Particleboard (PB)	791.49	20750
TV Unit	138.00	35.00	50.00	Dark color	Particleboard (PB)	834.00	20680
Coffee Table	33.50	33.50	46.00	Light color	Particleboard (PB)	310.00	20657
Coffee Table	33.00	33.00	46.00	Dark color	Medium-density FB	575.00	20336
TV Unit	180.00	35.00	48.60	Dark color	Particleboard (PB)	1966.00	20134
TV Unit	180.00	35.00	48.00	Dark color	Particleboard (PB)	1668.00	19922
TV Unit	180.00	35.00	54.00	Dark color	Particleboard (PB)	2019.00	19628
TV Unit	120.00	30.00	50.00	Light color	Particleboard (PB)	749.00	19298
Coffee Table	34.00	34.00	49.00	Light color	Particleboard (PB)	289.00	19209
TV Unit	180.00	30.00	47.00	Light color	Medium-density FB	1589.00	19123
TV Unit	180.00	44.50	44.60	Light color	Medium-density FB	1973.00	18683
TV Unit	150.00	29.50	44.10	Dark color	Medium-density FB	1019.00	18330
Coffee Table	45.00	18.00	35.00	Light color	Medium-density FB	629.00	17621
TV Unit	140.00	30.00	39.00	Light color	Particleboard (PB)	830.00	16703
Coffee Table	34.00	34.00	49.00	Dark color	Particleboard (PB)	289.00	16562
TV Unit	150.00	35.00	58.00	Light color	Medium-density FB	2469.00	16539
TV Unit	120.00	35.00	61.00	Dark color	Particleboard (PB)	412.00	16501
Coffee Table	55.00	34.50	51.00	Dark color	Medium-density FB	414.00	16342
TV Unit	180.00	29.60	49.00	Light color	Particleboard (PB)	915.00	16237
Coffee Table	60.00	41.00	52.00	Dark color	Particleboard (PB)	2150.00	16029
TV Unit	180.00	35.00	60.00	Light color	Particleboard (PB)	2450.00	15688
TV Unit	120.00	29.50	40.00	Light color	Particleboard (PB)	650.00	15537
TV Unit	180.00	35.00	49.00	Light color	Particleboard (PB)	1374.00	15471
Coffee Table	60.00	40.00	45.00	Dark color	Medium-density FB	806.00	15231
Coffee Table	45.00	35.00	40.00	Light color	Medium-density FB	289.00	15062
Coffee Table	34.00	34.00	49.00	Dark color	Medium-density FB	289.00	14979
Coffee Table	40.00	35.00	40.00	Dark color	Particleboard (PB)	291.00	14843
TV Unit	180.00	35.00	45.00	Light color	Particleboard (PB)	1295.00	14601
TV Unit	180.00	35.00	48.30	Dark color	Particleboard (PB)	1475.00	14448
Coffee Table	35.00	18.00	51.00	Dark color	Particleboard (PB)	399.00	14276

TV Unit	180.00	35.00	48.30	Light color	Particleboard (PB)	1562.00	14160
Coffee Table	34.00	34.00	49.00	Light color	Medium-density FB	289.00	13455
TV Unit	180.00	30.00	50.00	Light color	Particleboard (PB)	1100.00	13440
Coffee Table	60.00	60.00	46.00	Light color	Medium-density FB	599.00	13401
TV Unit	150.00	30.00	44.00	Dark color	Particleboard (PB)	1150.00	13116
Coffee Table	34.00	34.00	49.00	Dark color	Medium-density FB	289.00	13012
Coffee Table	40.00	60.00	47.00	Dark color	Particleboard (PB)	579.00	12964
TV Unit	180.00	30.00	45.00	Light color	Particleboard (PB)	1600.00	12871
TV Unit	180.00	30.00	47.00	Light color	Particleboard (PB)	1560.00	12834
Coffee Table	60.00	40.00	51.00	Dark color	Medium-density FB	600.00	12705
Coffee Table	40.00	75.00	50.00	Dark color	Particleboard (PB)	749.00	12332
TV Unit	120.00	30.00	50.00	Light color	Particleboard (PB)	700.00	12229
TV Unit	180.00	35.00	48.30	Light color	Particleboard (PB)	1600.00	12220
TV Unit	210.00	36.80	46.80	Light color	Particleboard (PB)	3100.00	11920
Coffee Table	33.00	33.00	52.00	Light color	Particleboard (PB)	349.00	11812
TV Unit	180.00	35.00	48.30	Light color	Particleboard (PB)	2230.00	11760
Coffee Table	65.00	42.00	54.00	Light color	Medium-density FB	1604.00	11728
TV Unit	120.00	30.00	45.00	Light color	Particleboard (PB)	650.00	11579
Coffee Table	33.00	33.00	46.00	Light color	Medium-density FB	310.00	11565
TV Unit	168.00	37.00	51.60	Dark color	Particleboard (PB)	3309.00	11488
TV Unit	140.00	50.00	60.00	Dark color	Particleboard (PB)	815.00	11460
TV Unit	150.00	30.00	40.60	Dark color	Particleboard (PB)	1378.00	11383
Coffee Table	72.50	38.00	48.00	Dark color	Particleboard (PB)	835.00	11356
TV Unit	138.00	29.50	42.60	Dark color	Particleboard (PB)	740.00	11354
TV Unit	150.00	35.00	53.00	Light color	Particleboard (PB)	1189.00	11189
TV Unit	130.00	30.00	40.00	Light color	Particleboard (PB)	640.00	11146
TV Unit	140.00	33.00	40.00	Light color	Particleboard (PB)	680.00	11127
Coffee Table	31.50	45.00	40.00	Light color	Particleboard (PB)	354.00	10932
TV Unit	200.00	29.00	43.00	Light color	Particleboard (PB)	1999.00	10867
Coffee Table	35.00	18.00	40.00	Light color	Particleboard (PB)	354.00	10748
TV Unit	150.00	30.00	44.00	Light color	Particleboard (PB)	1450.00	10553
TV Unit	180.00	35.00	48.30	Dark color	Particleboard (PB)	1310.00	10539
TV Unit	160.00	30.00	50.00	Dark color	Particleboard (PB)	990.00	10452
TV Unit	180.00	35.00	58.00	Dark color	Medium-density FB	2750.00	10356
Coffee Table	60.00	44.00	46.00	Light color	Medium-density FB	529.00	10233
TV Unit	140.00	30.00	39.00	Light color	Particleboard (PB)	830.00	10145
TV Unit	178.00	34.00	60.00	Dark color	Medium-density FB	1230.00	10020
Coffee Table	65.00	45.00	54.00	Light color	Medium-density FB	1604.00	10015
Coffee Table	38.00	18.00	51.00	Dark color	Medium-density FB	605.00	9849
TV Unit	120.00	30.00	50.00	Dark color	Particleboard (PB)	1200.00	9787
TV Unit	140.00	30.00	39.00	Dark color	Particleboard (PB)	750.00	9728
TV Unit	180.00	30.00	50.00	Dark color	Particleboard (PB)	1100.00	9602
TV Unit	120.00	29.00	46.00	Light color	Particleboard (PB)	450.00	9577
TV Unit	180.00	29.60	49.00	Light color	Particleboard (PB)	1580.00	9437
TV Unit	138.00	29.50	48.60	Light color	Particleboard (PB)	805.00	9402
TV Unit	160.00	30.00	45.00	Dark color	Particleboard (PB)	1070.00	9342
Coffee Table	53.00	35.00	52.00	Light color	Medium-density FB	459.00	9331
TV Unit	180.00	40.00	35.00	Dark color	Medium-density FB	1980.00	9247
TV Unit	180.00	30.00	44.00	Light color	Medium-density FB	1530.00	9167
TV Unit	180.00	35.00	42.00	Dark color	Medium-density FB	1700.00	9070

TV Unit	180.00	35.00	53.00	Dark color	Medium-density FB	1370.00	9035
TV Unit	180.00	35.00	48.30	Light color	Medium-density FB	1860.00	9028
Coffee Table	35.00	35.00	49.00	Light color	Medium-density FB	289.00	9023
TV Unit	120.00	30.00	42.00	Light color	Particleboard (PB)	480.00	8890
TV Unit	180.00	35.00	40.00	Light color	MDF + PB	3570.00	8873
TV Unit	180.00	44.50	44.60	Dark color	Medium-density FB	1980.00	8787
TV Unit	150.00	30.00	30.00	Light color	Particleboard (PB)	800.00	8612
TV Unit	150.00	30.00	42.00	Dark color	Particleboard (PB)	800.00	8612
Coffee Table	35.00	35.00	51.00	Dark color	Medium-density FB	289.00	8534
Coffee Table	34.00	18.00	49.00	Light color	Medium-density FB	289.00	8510
TV Unit	143.00	30.00	44.00	Light color	MDF + PB	2380.00	8452
TV Unit	180.00	30.00	50.00	Dark color	Particleboard (PB)	1100.00	8355
TV Unit	180.00	350.00	48.30	Dark color	MDF + PB	2410.00	8204
Coffee Table	60.00	44.00	46.00	Dark color	Medium-density FB	529.00	8106
Coffee Table	60.00	37.00	46.00	Light color	Particleboard (PB)	529.00	8098
TV Unit	180.00	35.00	48.30	Dark color	Particleboard (PB)	1500.00	8042
TV Unit	180.00	45.00	44.00	Light color	Particleboard (PB)	915.00	7980
TV Unit	180.00	29.00	45.00	Light color	Particleboard (PB)	2200.00	7795
TV Unit	180.00	32.00	42.00	Dark color	Particleboard (PB)	820.00	7734
Coffee Table	50.00	37.00	46.00	Dark color	Medium-density FB	529.00	7583
TV Unit	180.00	35.00	50.00	Dark color	Particleboard (PB)	1170.00	7539
TV Unit	160.00	30.00	49.00	Light color	Particleboard (PB)	1170.00	7455
TV Unit	180.00	30.00	47.00	Dark color	MDF + PB	1560.00	7438
Coffee Table	34.00	34.00	49.00	Light color	Particleboard (PB)	289.00	7382
TV Unit	140.00	33.00	40.00	Light color	Particleboard (PB)	680.00	7323
TV Unit	180.00	35.00	54.00	Light color	Particleboard (PB)	1160.00	7266
Coffee Table	65.00	42.00	57.00	Dark color	Medium-density FB	1699.00	7242
Coffee Table	33.50	33.50	46.00	Dark color	Medium-density FB	310.00	7214
TV Unit	180.00	30.00	46.00	Light color	Particleboard (PB)	1600.00	7154
Coffee Table	60.00	39.00	52.00	Dark color	Particleboard (PB)	615.00	7093
Coffee Table	60.00	44.00	46.00	Dark color	Particleboard (PB)	529.00	7038
Coffee Table	62.00	32.00	56.00	Light color	Particleboard (PB)	1999.00	6946
TV Unit	140.00	30.00	39.00	Dark color	Particleboard (PB)	715.00	6923
TV Unit	180.00	35.00	49.00	Light color	MDF + PB	2170.00	6922
Coffee Table	34.00	34.00	49.00	Dark color	Medium-density FB	289.00	6904
Coffee Table	60.00	37.00	46.00	Light color	Particleboard (PB)	529.00	6849
Coffee Table	33.00	33.00	46.00	Dark color	Medium-density FB	310.00	6820
TV Unit	270.00	30.00	29.00	Light color	MDF + PB	1600.00	6788
TV Unit	180.00	35.00	45.00	Light color	Particleboard (PB)	900.00	6749
TV Unit	120.00	35.00	50.00	Dark color	Particleboard (PB)	690.00	6744
TV Unit	180.00	35.00	54.00	Light color	MDF + PB	1450.00	6739
TV Unit	180.00	35.00	48.30	Light color	MDF + PB	1280.00	6712
Coffee Table	60.00	37.50	51.00	Dark color	Medium-density FB	665.00	6591
Coffee Table	60.00	37.00	46.00	Dark color	Particleboard (PB)	999.00	6584
Coffee Table	35.00	35.00	40.00	Light color	Particleboard (PB)	279.00	6336
Coffee Table	60.00	37.00	46.00	Light color	Particleboard (PB)	529.00	6335
Coffee Table	33.00	33.00	46.00	Dark color	Medium-density FB	575.00	5661
Coffee Table	35.00	18.00	40.00	Dark color	Medium-density FB	309.00	5654
Coffee Table	60.00	44.00	46.00	Dark color	Medium-density FB	529.00	5578
Coffee Table	75.00	40.00	50.00	Light color	Particleboard (PB)	749.00	5471

Coffee Table	73.00	41.00	57.50	Dark color	Medium-density FB	2700.00	5465
Coffee Table	60.00	37.00	46.00	Dark color	Medium-density FB	529.00	5465
Coffee Table	60.00	37.50	51.00	Light color	Medium-density FB	671.00	5454
Coffee Table	42.00	29.00	45.00	Light color	Medium-density FB	1604.00	5399
Coffee Table	33.00	33.00	46.00	Dark color	Medium-density FB	575.00	5265
Coffee Table	65.00	40.00	52.00	Light color	Medium-density FB	1100.00	5259
Coffee Table	60.00	44.00	46.00	Light color	Medium-density FB	529.00	5207
Coffee Table	33.00	33.00	52.00	Dark color	Particleboard (PB)	349.00	5178
Coffee Table	65.00	42.00	57.00	Light color	Medium-density FB	1604.00	5138
Coffee Table	55.00	34.50	51.00	Light color	Medium-density FB	414.00	5094
Coffee Table	50.00	35.00	44.00	Light color	Medium-density FB	534.00	5016
Coffee Table	40.00	18.00	35.00	Light color	Particleboard (PB)	289.00	4921
Coffee Table	31.00	18.00	44.00	Light color	Medium-density FB	319.00	4918
Coffee Table	75.00	40.00	54.00	Dark color	Medium-density FB	747.00	4904
Coffee Table	75.00	40.00	50.00	Light color	Particleboard (PB)	749.00	4330
Coffee Table	60.00	40.00	47.00	Light color	Particleboard (PB)	579.00	4181
Coffee Table	33.00	33.00	46.00	Dark color	Medium-density FB	310.00	4061
Coffee Table	40.00	30.00	40.00	Light color	Medium-density FB	319.00	4035
Coffee Table	60.00	37.50	51.00	Light color	Particleboard (PB)	650.00	3914
Coffee Table	65.00	42.00	57.00	Light color	Medium-density FB	1604.00	3899
Coffee Table	34.00	34.00	49.00	Light color	Medium-density FB	289.00	3889
Coffee Table	60.00	40.00	47.00	Light color	Particleboard (PB)	579.00	3773
Coffee Table	60.00	41.00	52.00	Light color	Particleboard (PB)	2150.00	3751
Coffee Table	31.50	45.00	40.00	Dark color	Medium-density FB	354.00	3724
Coffee Table	33.80	18.00	52.00	Light color	Medium-density FB	700.00	3684
Coffee Table	39.00	39.00	55.00	Dark color	Particleboard (PB)	1699.00	3678
Coffee Table	40.00	44.00	50.00	Dark color	Medium-density FB	1199.00	3669
Coffee Table	66.00	40.50	53.50	Dark color	Medium-density FB	1548.00	3662
Coffee Table	34.00	34.00	49.00	Light color	Medium-density FB	289.00	3613
Coffee Table	55.00	32.00	58.00	Dark color	Medium-density FB	654.00	3606
Coffee Table	60.00	40.00	49.00	Dark color	Medium-density FB	810.00	3597
Coffee Table	39.00	39.00	51.00	Dark color	Particleboard (PB)	648.00	3580
Coffee Table	61.00	45.00	51.00	Light color	Medium-density FB	1388.00	3575
Coffee Table	40.00	35.00	45.00	Light color	Medium-density FB	279.00	3561
Coffee Table	108.00	40.00	46.00	Dark color	Medium-density FB	649.00	3555
TV Unit	145.00	36.00	50.00	Light color	Particleboard (PB)	1000.00	725
TV Unit	150.00	30.00	45.00	Dark color	Particleboard (PB)	1654.00	500
TV Unit	180.00	44.00	30.00	Dark color	Particleboard (PB)	2550.00	499
TV Unit	150.00	31.00	52.00	Dark color	Particleboard (PB)	2049.00	406
TV Unit	180.00	40.00	48.00	Light color	Medium-density FB	4134.00	397
TV Unit	180.00	37.00	40.00	Dark color	Particleboard (PB)	2790.00	384
TV Unit	180.00	29.00	49.00	Dark color	Particleboard (PB)	2140.00	359
TV Unit	180.00	40.00	53.00	Light color	Medium-density FB	4163.00	345
TV Unit	180.00	36.00	52.00	Light color	Particleboard (PB)	1960.00	285
TV Unit	180.00	30.00	45.00	Light color	Particleboard (PB)	2790.00	282
TV Unit	200.00	40.00	42.00	Dark color	Medium-density FB	22079.00	218
TV Unit	240.00	35.00	35.00	Light color	Medium-density FB	4208.00	189
TV Unit	220.00	40.00	50.00	Light color	Medium-density FB	5077.00	183