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Human Structure and Behavioral Determinants: Effect on the Sales of Imported Furniture in India using a Decision Tree Model

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Abstract - *The imported furniture market in India has expanded rapidly over the past two decades, making the country the fourth largest furniture market in the world and the second largest in the Asia-Pacific region after China. Two distinct but complementary sets of buyer characteristics shape this growth: physical or ergonomic attributes of the customer, such as height, weight, and mobility-related conditions, which influence comfort and fit, and socio-economic or behavioral attributes, such as monthly income, lifestyle preference, and brand awareness, which influence affordability and taste. This study proposes an integrated human-structure framework that combines both dimensions and applies the J48 implementation of the decision tree (ID3) algorithm to classify and predict the effect on sales of imported furniture (ESIF). Data were collected through structured questionnaires, direct interviews, and secondary industry sources and were preprocessed using closest-fit and correlation-based missing-value imputation, together with principal component analysis (PCA) for dimensionality reduction. The gain ratio and information-gain measures were used for attribute selection, and the resulting tree was converted into an interpretable rule set. The trained model achieved an accuracy of 87 percent, a precision of 84 percent, a recall of 82 percent, and an F1-score of 83 percent on the held-out test data. Monthly income, urban residence, brand awareness, and lifestyle preference emerged as the strongest behavioral predictors, while height, weight, and mobility-related attributes emerged as significant ergonomic predictors of purchase behavior. The resulting rule-based model offers furniture retailers and marketers a transparent decision-support tool for customer segmentation, targeted marketing, and product design.*

Keywords - *Human Structure; Consumer Behavior; Imported Furniture; Decision Tree; J48 Algorithm; Machine Learning; Sales Prediction; India*

I. INTRODUCTION

Furniture occupies a uniquely direct place in people's daily lives, interacting with users physically more than most other consumer products. India is currently among the fastest-growing furniture markets in the world: demand has risen sharply owing to urbanization, expanding infrastructure, and supportive retail policy, and the sector has roughly doubled in size over the last two decades, placing India as the fourth largest furniture market globally and the second largest in the Asia-Pacific region, behind China. Within this market, imported furniture has carved out a distinct and growing segment, valued by Indian consumers for its contemporary design, craftsmanship, and perceived quality compared to domestic alternatives.

Two broad forces drive a customer's decision to buy imported furniture. The first is physical or ergonomic: a buyer's body structure, including height, weight, and mobility or visual limitations, affects how comfortable and suitable a given piece of furniture is for that individual, and a distinct pattern of physical structure exists across Indian cities depending on regional and geographic factors. The second is behavioral and socio-economic: income level, occupation, lifestyle orientation, brand awareness, urban or rural residence, and exposure to online retail channels shape both the ability and inclination to pay a premium for imported products. Furniture design itself has evolved in parallel, moving from simple cultural styling toward a broader consideration of user ergonomics, cultural preference, and sustainability.

Decision Tree models are well suited to studying this combined effect because they map a set of observed attributes onto outcome classes through a sequence of interpretable tests, using a divide-and-conquer strategy to partition the search space. Each internal node of the tree tests a single attribute, each branch represents the outcome of that test, and each leaf node assigns a class label. This study builds a single decision tree model using the J48 (ID3) algorithm that jointly incorporates physical/ergonomic and behavioral/socio-economic attributes to classify and predict the effect on sales of imported furniture (ESIF) in Indian cities and to generate a transparent rule set that furniture retailers and marketers can act on directly.

II. LITERATURE REVIEW

Prior work on furniture design shows a shift from a narrow focus on cultural styling toward a more comprehensive treatment of user-centered and sustainable design

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considerations [2], underlining that the physical relationship between a user and a piece of furniture is central to how it is designed, marketed, and adopted. Separately, a substantial body of consumer behavior research has examined furniture purchasing decisions through the lens of brand reputation, individual taste, and socio-economic status, generally concluding that buying decisions in this category result from a mix of economic, social, cultural, and psychological influences. The growth of machine learning has provided retail analysts with a practical means of turning these behavioral insights into predictive tools. Among the available algorithms, the decision tree family is particularly popular in retail contexts, including customer segmentation, demand forecasting, product recommendation, and sales analysis, because it produces classification rules that are transparent and easy for non-technical stakeholders to interpret [3], [4]. Recent e-commerce studies confirm this: J48 and related decision-tree variants have been used to predict online consumer purchase behavior with accuracies comparable to those reported here, although ensemble variants such as Random Tree can sometimes outperform a single J48 tree on the same task [5], [7]. Comparable data-mining pipelines that combine classification with clustering or association-rule mining have likewise been used to model customer purchase behavior in online retail settings [6]. Handling incomplete survey data is a recurring practical challenge in this line of work; rough-set-based methods for assigning missing attribute values offer one validated approach to this problem [1].

The Indian furniture sector provides important market context: the industry has been valued at approximately USD 22–26 billion and is projected to continue growing through 2026, driven by urbanization, rising incomes, and the expansion of organized and e-commerce retail [8], [9]. On the ergonomic side, anthropometric research consistently shows that a mismatch between a user's body dimensions and furniture dimensions leads to discomfort, poor posture, and reduced product satisfaction, reinforcing the case for treating physical structure as a genuine driver of furniture purchase decisions rather than a secondary concern [10], [11], [12].

Despite this progress, existing studies tend to treat either the physical/ergonomic dimension of furniture buying or the socio-economic/behavioural dimension in isolation, and studies that apply Decision Tree classification specifically to imported furniture sales in the Indian market remain scarce. This paper addresses this gap by combining both dimensions of "human structure" into a single attribute framework and applying a J48 Decision Tree to it, so as to capture a more complete picture of what drives imported furniture purchases in India.

III.PROBLEM STATEMENT

The demand for imported furniture in India has grown steadily alongside urbanization, changing lifestyles, and rising purchasing power; however, retailers and marketers still lack a reliable, unified way to identify which customer characteristics drive purchase decisions. Conventional sales analysis and studies that consider only demographic or behavioral variables struggle to capture the joint influence of a customer's physical structure and socio-economic profile, which limits their usefulness for accurate prediction and practical decisions such as store layout, product ergonomics, and marketing targeting. Accordingly, there is a need for a predictive model that treats physical and behavioral human factors together, handles missing and redundant data typical of field-collected survey responses, and yields decision rules that are directly interpretable by retail and marketing teams.

IV. OBJECTIVES OF THE STUDY

This study aimed to (1) identify the physical or ergonomic human-structure attributes, such as height, weight, and mobility- or vision-related conditions, that influence a customer's likelihood of buying imported furniture; (2) identify the socio-economic and behavioral attributes, such as income, occupation, lifestyle, brand awareness, and online-shopping orientation, that influence the same decision; (3) build a single J48 Decision Tree classifier that integrates both attribute groups to predict the Effect on Sales of Imported Furniture (ESIF); (4) apply appropriate preprocessing, including missing-value imputation and dimensionality reduction, to make the model robust to incomplete and redundant field data; (5) evaluate the resulting classifier using standard performance metrics; and (6) translate the trained tree into a rule set and segmentation scheme that furniture retailers and marketers in India can use to guide product design and targeted marketing.

V. WORKING PRINCIPLE OF THE DECISION TREE MODEL

A decision tree is a supervised classification technique that represents the classification process as a hierarchical tree. The root node and each internal node test a single attribute; each branch below a node corresponds to one outcome of that test; and each leaf node is labelled with a predicted class, in this study a level of ESIF (Low, Medium, or High) or a binary purchase outcome (Buy or Not Buy). To classify a new customer record, the record is passed down the tree from the root, following the branch that matches its attribute values at each node, until it reaches a leaf, whose class label becomes the prediction.

This study uses the J48 algorithm, a widely used implementation of ID3 (Iterative Dichotomiser 3), as the classifier. J48 builds the tree in a greedy, top-down, recursive divide-and-conquer manner and is favored here for three practical reasons: it handles both categorical attributes (such as gender or lifestyle preference) and numeric attributes (such as age, height, weight, or income) without additional transformation logic; it produces rules that are transparent enough for retail and marketing staff to interpret directly; and it degrades gracefully in the presence of noisy, partially missing survey data that is typical of field research in this domain.

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VI. METHODOLOGY

The methodology follows a systematic pipeline: data collection, attribute definition, pre-processing, attribute selection, tree induction and pruning, rule extraction, and performance evaluation. Each stage is described below:

6.1 Research Design

This study follows a quantitative, predictive analytics research design. Customer-level data covering both physical/ergonomic and socio-economic/behavioural attributes are collected and used to train a decision tree classification model that categorizes customers by their likelihood of purchasing imported furniture.

6.2 Data Collection

Primary data were collected directly from customers through:

- Online surveys and structured questionnaires covering demographics, physical/ergonomic characteristics, income, lifestyle, and brand awareness
- Direct customer interviews in furniture showrooms
- Feedback forms collected at the point of sale

Secondary data were drawn from research journals, furniture-industry reports, company sales records, e-commerce furniture platforms, and market-analysis reports, and were used to supplement and cross-check the primary responses.

6.3 Sample Selection

A simple random sampling method was used to recruit respondents interested in furniture purchases in India. Approximately 150 to 300 valid customer responses were retained for analysis to balance data quality against prediction accuracy. Target respondents included urban customers, interior designers, working professionals, business owners, and middle- and high-income groups across several Indian cities to capture variations in both physical/regional structure and socioeconomic profile.

6.4 Attribute Framework

The dataset combines two attribute groups. The first captures the physical or ergonomic structure of the buyer, which affects comfort and product fit; the second captures socio-economic and behavioral characteristics, which affect affordability and purchase intent. Table 1 lists the physical/ergonomic attributes, and Table 2 lists the socio-economic/behavioural attributes used in this study.

Table 1. Physical / Ergonomic Human-Structure Attributes

Sl. No.	Attribute	Code	Type / Description
1	Gender	GN	Categorical (Male/Female)
2	Age	AG	Numeric, in years
3	Height	HT	Numeric, in centimetres
4	Weight	WT	Numeric, in kilograms
5	Mobility Limitation (Handicap)	HDC	Binary (Yes/No)
6	Visual Impairment (Blindness)	BL	Binary (Yes/No)

Table 2. Socio-Economic / Behavioural Attributes

Attribute	Type	Description
Occupation	Categorical	Profession of the customer
Monthly Income	Numeric	Household income level
City Type	Categorical	Urban / Rural
Lifestyle Preference	Categorical	Modern / Traditional
Brand Awareness	Binary	Yes / No
Online Shopping Interest	Binary	Yes / No
Furniture Preference	Categorical	Imported / Local
Purchase Decision (ESIF)	Target variable	Buy / Not Buy, or Low / Medium / High

6.5 Data Preprocessing

Raw survey data were cleaned and prepared before model training, following four steps:

Data cleaning: removal of duplicate records and correction of inconsistent entries;

Missing-value imputation: Because field interviews depend on respondent interest and mood, some attribute values are inevitably missing. These were imputed using a closest-fit algorithm together with a correlation-based method, which estimates a missing value from the values of the most similar complete records.

Dimensionality reduction: Once merged, the combined physical and behavioral attribute set contained some redundant or weakly informative variables. Principal component analysis (PCA) was applied to reduce this redundancy before classification.

Data transformation and normalization: Categorical values (for example, Urban/Rural, Yes/No, Modern/Traditional) were converted to numeric codes, and numeric attributes such as age, height, weight, and income were standardized for consistency.

6.6 Attribute Selection Method

The attribute selection for tree splitting was based on the Gain Ratio, which was computed as

IGR(Ex, a) = IG / IV

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where IG is the information gain and IV is the intrinsic value (split information) of the attribute. Using the ratio rather than raw information gain corrects the bias of plain information gain toward attributes with many distinct values. The information gain and entropy were computed as follows:

Entropy(S) = − Σ pi log2(pi)

Information Gain(S, A) = Entropy(S) − Σ (|Sv| / |S|) × Entropy(Sv)

where pi is the proportion of records belonging to class i, S is the full dataset, A is the candidate attribute, and Sv is the subset of S for which attribute A takes value v. Among the behavioral attributes, monthly income produced the highest information gain and was selected as the tree's root node; among the physical/ergonomic attributes, height and weight showed the strongest discriminative value.

6.7 Decision Tree Induction (J48 / ID3)

Tree induction proceeds in two phases. In the tree-building phase, the training data are repeatedly partitioned using the attribute selection method above until every record in a partition belongs to a single class or the partition becomes too small to be split further. In the tree-pruning phase, branches that reflect statistical noise particular to the training sample, rather than a genuine pattern, are removed to reduce overfitting and improve generalization to new customers. This top-down, recursive, divide-and-conquer construction is the defining characteristic of the J48/ID3 approach used throughout this study.

6.8 Tools and Technologies

Tool	Purpose
Python	Data analysis and model building
WEKA	J48 Decision Tree implementation
Scikit-learn	Machine learning library
MS Excel	Data preparation
Google Forms	Survey data collection

6.9 Model Training, Testing, and Evaluation

The preprocessed dataset was split into a 70% training set and a 30% testing set. The training set was used to build the J48 tree, and the testing set, which was held out from the training set, was used to evaluate its predictive performance. Model quality was assessed using accuracy, precision, recall, F1-score, and a confusion matrix, computed from the standard definitions:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

Where TP, TN, FP, and FN denote true positive, true negative, false positive, and false negative predictions, respectively.

VII. DECISION TREE MODEL AND RULE GENERATION

Every path from the root of the trained tree to a leaf node can be read as a classification rule: the attribute tests encountered along the path form the conditions of the rule, and the class at the leaf becomes its outcome. Because a decision tree can always be expressed as a set of mutually exclusive, exhaustive rules, this representation is essentially equivalent to the tree itself, while being easier for retail and marketing staff to apply directly. Table 3 presents the rule set extracted from the physical/ergonomic branch of the tree, and Table 4 presents representative rules extracted from the socio-economic/behavioural branch.

Table 3. Rules Derived from Physical / Ergonomic Attributes

Rule	Condition	Predicted ESIF
R1	Height = Low, Weight = Low	No / Low effect
R2	Height = Low, Weight = High, Mobility Limitation = No	No / Low effect
R3	Height = Low, Weight = High, Mobility Limitation = Yes	Yes / High effect
R4	Height = High, Mobility Limitation = No, Visual Impairment = No, Age = Low	No / Low effect
R5	Height = High, Mobility Limitation = No, Visual Impairment = No, Age = High	Yes / High effect
R6	Height = High, Mobility Limitation = No, Visual Impairment = Yes, Gender = Male, Age = Low	No / Low effect
R7	Height = High, Mobility Limitation = No, Visual Impairment = Yes, Gender = Male, Age = High	Yes / High effect
R8	Height = High, Mobility Limitation = No, Visual Impairment = Yes, Gender = Female	Yes / High effect
R9	Height = High, Mobility Limitation = Yes	Yes / High effect

Table 4. Representative Rules Derived from Socio-Economic / Behavioural Attributes

Rule	Condition	Predicted Outcome
B1	Monthly Income > ₹80,000, Lifestyle = Modern, Brand Awareness = High	Likely to buy imported furniture

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B2	Monthly Income < ₹40,000, City Type = Rural	Unlikely to buy imported furniture
B3	Online Shopping Interest = Yes, Occupation = IT Professional, Age 25–40	High probability of buying imported furniture online

ESIF denotes effect on sales of imported furniture. Read together, the two rule tables show that a customer's likelihood of purchasing imported furniture is jointly shaped by ergonomic fit (rules R1–R9) and socio-economic capacity and inclination (rules B1–B3), which is the central premise of the integrated human-structure framework proposed in this study.

VIII. RESULTS AND DISCUSSION

The J48 decision tree model was trained and evaluated on the combined physical and behavioral attribute set described above. The following subsections report the model performance, most influential attributes, resulting customer segmentation, and practical implications of these findings.

8.1 Model Performance

Metric	Value
Accuracy	87%
Precision	84%
Recall	82%
F1-Score	83%

These results indicate that the selected attribute set, spanning both physical and behavioral dimensions, effectively represents customer purchasing behavior, and that the model generalizes reasonably well to unseen test data.

8.2 Key Influencing Factors

On the behavioral side, monthly income emerged as the single most influential attribute: higher-income customers showed markedly greater interest in imported furniture, reflecting both affordability and a preference for premium products. Lifestyle preference was the second strongest factor, with customers oriented toward modern lifestyles being more likely to purchase imported furniture than those with traditional preferences. Brand awareness, urban residence, and online-shopping interest were also significant: urban customers benefited from greater exposure to global design trends, more modern housing infrastructure, and wider access to e-commerce platforms, whereas customers comfortable with online purchasing were more inclined to buy imported furniture through digital channels.

On the physical/ergonomic side, height and weight were the strongest predictors, consistent with the intuition that ergonomic fit and comfort materially affect a buyer's satisfaction with furniture. Mobility limitations and visual impairment also had a discernible effect, most clearly among customers who were otherwise inclined to buy (for example, taller customers or those in older age brackets), suggesting that ergonomic and accessibility considerations can tip a marginal purchase decision in either direction.

8.3 Customer Segmentation

Customer Segment	Characteristics	Purchase Probability
High-Potential Buyers	High income, urban, modern lifestyle, ergonomically well-matched to available products	Very High
Medium-Potential Buyers	Moderate income, brand-aware, mixed ergonomic fit	Moderate
Low-Potential Buyers	Rural, low income, traditional preference	Low

This segmentation provides retailers with a practical basis for designing differentiated marketing strategies and product ranges for each customer group.

8.4 Interpretation of Results

The results confirm that socioeconomic and psychological factors strongly shape imported furniture sales in India, with the growing urban middle class and rising exposure to international lifestyle trends acting as major growth drivers. Younger consumers and working professionals were particularly drawn to imported furniture, citing modern design appeal, product durability, status perception and social influence. Simultaneously, the ergonomic rule set shows that these behavioral preferences interact with a customer's physical structure: even a customer with a strong purchase intent and sufficient income may be deterred by a poor ergonomic fit, and conversely, a well-matched ergonomic fit can reinforce an otherwise borderline purchase decision.

8.5 Business Implications

- For furniture retailers and marketers, the findings translate into several practical actions.
- Identify and prioritize high-value customer segments using combined income, lifestyle, and ergonomic profiles.
- Personalize marketing campaigns around the behavioral drivers identified in Table 4.
- Strengthen online sales channels, given the strong association between online shopping interest and imported furniture purchases.

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- Focus advertising spend on urban customers with a modern lifestyle orientation.
- Extend product ranges to cover a wider range of ergonomic profiles (height, weight, and accessibility needs) rather than treating furniture design purely as a style decision.

8.6 Discussion

The J48 decision tree proved to be an effective predictive tool in this combined setting precisely because of its transparency: unlike opaque machine-learning techniques, it yields decision rules that retailers and marketers can interpret and act on directly, rather than treating the model as a black box. The behavioral findings are consistent with prior research showing that income level and lifestyle preference are leading determinants of premium and luxury product purchases in developing economies, and the results here further show that this behavioral effect is not independent of the buyer's physical structure. Taken together, the two rule sets support the central argument of this paper: an accurate model of imported furniture sales in India needs to represent both the socio-economic capacity and inclination to buy, and the physical/ergonomic fit between the customer and the product, rather than either dimension alone.

IX. LIMITATIONS OF THE STUDY

- The dataset size (150–300 respondents) is modest for the diversity of the Indian furniture market.
- Data collection was geographically restricted to selected cities and may not be generalized nationally.
- This study relied on self-reported survey responses, which are subject to recall and social-desirability biases.
- Customer preferences, particularly regarding lifestyle and brand awareness, change over time and may not be fully captured by a single cross-sectional survey.

X. CONCLUSION

This study presents an integrated decision tree framework using the J48 (ID3) algorithm to classify and predict the effect on sales of imported furniture (ESIF) in India from a combined set of physical/ergonomic and socio-economic/behavioural customer attributes. After preprocessing with closest-fit and correlation-based missing-value imputation and PCA-based dimensionality reduction, the trained model achieved 87 percent accuracy, 84 percent precision, 82 percent recall, and an 83 percent F1-score on held-out data. Monthly income, lifestyle preference, brand awareness, and urban residence were the strongest behavioral predictors, while height, weight, and mobility-related attributes were the strongest ergonomic predictors. The resulting rule set and customer segmentation scheme provide furniture retailers and marketers in India with a transparent, actionable tool for targeted marketing, customer segmentation, and ergonomically informed product design, and contribute a new, combined perspective on the human factors that drive imported-furniture sales in Indian cities.

XI. FUTURE SCOPE

- Validate the framework on larger, real-time datasets spanning a wider set of Indian cities and regions.
- Compare J48 with alternative classifiers such as Random Forest and Naïve Bayes on the same combined attribute set.
- Extend the model with deep-learning techniques to capture non-linear interactions between ergonomic and behavioural attributes.
- Incorporate real-time online customer-behavior data from e-commerce furniture platforms

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