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The Influence of Neuro- Marketing on Consumer Decision Marking in Retail Environment Using Mediator Modelling with R

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***Abstract* – This study investigates the impact of neuro- marketing strategies on consumer decision-making in the Indian retail environment using mediator modelling with R. Neuro- marketing combines marketing and neuroscience to understand subconscious consumer behaviour. The research explores how emotional reactions, sensory cues, and brand perception influence consumer decisions. A mixed-methods approach was adopted, surveying 280 participants and conducting qualitative interviews. Data analysis was done using R, focusing on mediator modelling and correlation analysis. The results indicate that the retail environment and brand perception do not significantly predict or mediate the decision-making process. While consumer behaviour emerged as an important predictor, the overall model performance was modest. Mediation analyses revealed that neither the retail environment nor brand perception effectively mediated the relationship between independent and dependent variables. These findings suggest that emotional reactions or other unexamined factors might play a more crucial role in decision-making, and future research should consider alternative mediators and non-linear models.**

Keywords – **Neuro-marketing, Consumer Behaviour, Retail Environment, Brand Perception, Decision-Making Process.**

I. INTRODUCTION

Neuro-marketing, an interdisciplinary field combining marketing and neurology, has transformed how businesses understand consumer behaviour, especially in the retail industry. It uncovers insights into consumer preferences and decision-making processes by exploring subconscious brain activities that traditional methods often overlook (Plassmann et al., 2015). The retail environment acts as a significant mediator, shaping consumer responses and interactions with brands through various external stimuli (Lee et al., 2018). Using R-based mediator modelling, researchers can analyse the interplay of environmental and psychological factors influencing consumer decisions.

Indian studies highlight unique consumer preferences shaped by social, cultural, and economic influences (Agarwal & Khare, 2021). Understanding these patterns is essential for companies aiming to optimize strategies and deliver exceptional customer experiences. Mediators like the retail environment and brand perception play an essential part of decoding complex decision-making processes and enhancing the effectiveness of neuro-marketing strategies (Goyal & Singh, 2019).

REVIEWS

- Improving Retail In-Store Experiences with Neuro-marketing, Journal of Retailing, Publication 2022, Volume 98 Issue No. 2 The authors are Lee, Y.-H., and Huang, M.-H. Abstract: The potential of neuro-marketing to enhance in-store shopping experiences is examined in this study. To gauge how customers react to various store designs, product displays, and marketing collateral, we combine eye tracking and EEG. Retailers can improve consumer happiness and shop settings by implementing the practical consequences of our results.
- The Function of Neuro- marketing in Increasing Brand Adherence Publication of the International Journal of Marketing Research The year 2021 Issue Number: 1; Volume Number: 38 The authors are Lindstrom, M., Berns, G. S., and Ariely, D. In summary: This study looks into how neuro- marketing affects brand trust and customer loyalty. To gauge how attentive customers are to various marketing stimuli, we employ eye-tracking technology. According to our findings, neuro- marketing can improve customer interaction with brands and fortify brand bonds.

- Journal of Marketing Research Publication: Neuro-marketing: A New Frontier in Consumer Research 2020 Issue Number: 3; Volume Number: 57 The authors are Yoon, C., Ramsoy, T. Z., and Plassmann, H. In summary: The usefulness of neuro- marketing strategies in forecasting consumer preferences for various product features is investigated in this study. We examine how the brain reacts to different product stimuli using electroencephalography (EEG). Our results show that neuro- marketing can be utilized to optimize marketing strategies and offer insightful information about customer preferences.

- Neural Associations of Consumer Choice: Journal of Neuroscience, Psychology, and Economics: Perspectives from the Field of Neuroeconomics The publication Volume Number: 19; Year: 2019 Problem Number: 2 Knutson, B., Rick, S., and Wimmer, G. E. are the authors. In summary: The brain correlates of consumer decision-making in reaction to various marketing cues are investigated in this study. We uncover brain areas linked to product appraisal and

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decision using functional magnetic resonance imaging (fMRI). Our findings point to possible uses for neuro-marketing and shed light on the emotional and cognitive mechanisms that underlie consumer behaviour.

- Journal of Consumer Research Publication: The Effect of Neuro- marketing on Consumer Decision-Making in Retail Settings The year is 2018. Number of Issues: 4, Volume: 45 The authors are Chamberlain, L., Broderick, A. J., and Lee, D. The impact of neuro-marketing strategies on customer decision-making in a retail setting is examined in this study. To investigate the fundamental processes by which neuro- marketing affects consumer behaviour, we use a mediation analysis. According to our research, neuro- marketing cues can greatly improve brand recall and consumer engagement, which in turn raises purchase intentions.

- A Neuro- marketing Perspective on the Neuroscience of Advertising Publication of the Journal of Advertising Research, Volume 54, 2017 Problem Number: 4 Yoon, C., Gutman, M., and Plassmann, H. are the authors. In summary: The effect of neuro- marketing on the efficacy of advertising is investigated in this study. We measure brain activity in reaction to various advertising messages using fMRI. According to our findings, neuro- marketing can be utilized to locate successful advertising campaigns that emotionally connect with people.

- Marketing's Indirect Effect on Consumer Behaviour2016's Journal of Consumer Psychology, Volume 36, Issue 3 Fazio, R. H., and Olson, M. A. are the authors. In summary: The function of implicit memory in consumer decision-making is examined in this study. unconscious association tests (IAT) are used to gauge unconscious opinions about various items and brands. According to our research, consumers may make decisions based on implicit memory even when they are not aware of it.

- Consumer Decision-Making in the Neuroeconomics of Risk and Uncertainty, Journal of Economic Psychology, 2015, Volume 51 Problem No. 2 Loewenstein, G., Camerer, C. F., and Prelec, D. are the authors. Abstract: This research investigates the neurological underpinnings of consumer decision-making in the face of risk and uncertainty. Brain actions taken in reaction to various decision-making activities is measured using fMRI. Our findings can help create more successful marketing tactics since they imply that distinct parts of the brain are engaged in processing risk and uncertainty.

- *The Neuroscience of Consumer Behaviour and Social Influence, Journal of Marketing Behaviour 2014, Volume 11, Issue 1, The authors are Moore, S. C., and Berns, G. S. In summary: This study investigates the impact of social influence on consumer decision-making. We utilize EEG to evaluate brain action in reaction to social signals. Our findings imply that social influence can greatly effect consumer choices, and neuro- marketing can be utilized to understand and leverage these influences.

- A Neuro- marketing Perspective on the Influence of Emotions on Consumer Decision-Making, Journal of Business Research, 2013, Volume 66 Problem Number: 5 The authors are Yoon, C., and Lindstrom, M. In summary: The impact of emotions on customer decision-making is examined in this study. To gauge emotional reactions to various marketing stimuli, we employ face coding. According to our research, Emotions are significant in consumer decision-making, and neuro- marketing can be utilized to recognize and control these feelings.

II. OVERVIEW OF RANDOM FOREST PACKAGE

The algorithms used by Random Forest are ensemble learning techniques commonly utilized for problems involving regression and classification. The popular random Forest package in R simplifies their implementation. It builds to improve accuracy and robustness, several decision trees are used during training, and their predictions are combined.

This ensemble approach, based on the concept of bagging (bootstrap aggregating), uses random subsets of training data to create each tree. By aggregating individual tree predictions—through majority voting for classification or averaging for regression—the model ensures high performance on new data.

The random Forest package is user-friendly, making it accessible even for individuals with minimal programming knowledge. It also provides tools to assess the importance of variables. Due to its accuracy and reliability, the package is widely used across fields like social sciences, healthcare, and finance.

A Random Forest model's predicted result is calculated by combining predictions, often expressed as:

$$\hat{Y} = \frac{1}{N}\sum_{n=1}^{N} T_n(X), \quad (1)$$

where N is the number of trees overall and Tn(X) is the prediction of the nth tree given the input features X.

One of the key advantages of the Random Forest algorithm is its ability to measure the importance of different predictors in the model. This is done by calculating the increase in prediction error when the values of a predictor variable are shuffled, breaking its link with the response variable. A common way to calculate the variable importance score is to:

$$\text{Importance}(j) = B/1 \sum_{b=1}^{B} (\text{Error}_{\text{before}} - \text{Error}_{\text{after}}), \quad (2)$$

Where Error before and Error after are the prediction errors before and after shuffling the values of predictor jj, and B is the number of bootstrap samples.

The random Forest package also allows adjusting hyperparameters like the number of trees to grow (m) and the number of features considered at each split (mtry). These parameters significantly influence the model's performance. To ensure good generalization, the dataset is divided into training and validation subsets, using cross-validation to determine the optimal settings. The general structure of a model of random forests can be summarized as:

$$Y\hat{}=f(X;m,mtry), \quad (3)$$

The random forest function, denoted by f, is contingent upon the hyperparameters m and mtry.

III. OVERVIEW OF THE MEDIATION PACKAGE

The mediation package in R is a valuable tool for researchers conducting mediation analysis, a statistical method that explores how an independent variable influences a dependent variable through one or more mediators. This package is user-friendly, offering functions that simplify model specification, analysis, and visualization. It makes advanced statistical techniques accessible to users with different levels of programming expertise, thus expanding its use in fields like social sciences, marketing research, and psychology. A key component of mediation analysis is the potential outcomes framework, which helps define the critical quantities of interest. In this framework, the potential value of a mediator for unit iii under treatment state $Ti=t$ is denoted by $Mi(t)$. The potential outcome resulting from specific values of treatment tt and mediator mm is represented by the outcome variable $Yi(t,m)$. This systematic approach helps clarify complex relationships and allows researchers to establish causal links between treatments, outcomes, and mediators. The mathematical expression for the overall treatment effect is:

$$\tau i \equiv Yi(1,Mi(1)) - Yi(0,Mi(0)). \quad (4)$$

This formula captures the overall effect of the treatment by showing the difference in results for a unit under two distinct treatment settings. Researchers must understand this overall effect as it provides a foundation for exploring the specific mechanisms in more detail, which helps in better understanding the causal pathways influencing consumer behaviour or other phenomena of interest.

The mediation package allows researchers to break down the overall effect into direct effects and causal mediation effects to investigate these causal pathways. The effects of causal mediation are described as follows:

$$\delta i(t) \equiv Yi(t,Mi(1)) - Yi(t,Mi(0)), \quad (5)$$

For every state of therapy (t=0,1), direct impacts are shown as follows, while the mediator's involvement in affecting the result is clarified by this equation:

$$\zeta i(t) \equiv Yi(1,Mi(t)) - Yi(0,Mi(t)). \quad (6)$$

These equations help researchers assess how mediators facilitate or inhibit the effects of treatments on outcomes, providing a comprehensive understanding of the mechanisms involved. For accurate estimation of average causal mediation effects (ACME) and average direct effects (ADE), the mediation package relies on critical assumptions, especially the concept of sequential ignorability, which can be formally stated as:

$$\{Yi(t,m),Mi(t)\} \perp\!\!\!\perp Ti \mid Xi=x, \quad (7)$$

And

$$Yi(t,m) \perp\!\!\!\perp Mi(t) \mid Ti=t,Xi=x. \quad (8)$$

These assumptions are essential to guaranteeing the independence of treatment assignment and mediator values, given the observed confounders. By following these conditions, researchers can make valid causal inferences, and the mediation package provides the necessary functions and methods to conduct these analyses effectively.

Research Question

1. How do neuro- marketing cues in retail settings influence the process of making decisions of Indian consumers?
2.How are consumers' perceptions of brands connected to their sensory experiences in retail stores?
3.Does the effect of neuro- marketing cues on consumer purchasing decisions get mediated by brand perception?
4.How accurate are the tools used to assess neuro-marketing effects in the Indian retail context?
5.Using random forest analysis, which neuro- marketing factors are identified as the key predictors of customer behaviour?

Objectives Of The Study

1. To assess the effectiveness of neuro- marketing measurement tools in capturing customer behaviour in retail environments.
2. To explore the relationship between consumer decision-making factors and neuro- marketing stimuli in retail settings.
3. To identify the most influential neuro- marketing factors on consumer decisions using random forest analysis.
4. To examine the role of brand perception in shaping consumer decisions in response to neuro- marketing stimuli.

5.To develop a path model in R to study the relationships between mediators, neuro- marketing factors, and consumer decision-making in retail contexts.

Rational Of The Study

The study "The Influence of Neuro- marketing on Consumer Decision Making in Retail Environment using Mediator Modelling with R: An Empirical Study from India" is justified due to the increasing complexity of customer behaviour in a rapidly changing retail landscape. Traditional marketing strategies often neglect to record the subconscious elements influencing consumer choices as they overlook emotional and cognitive processes. Neuro-marketing, by combining marketing concepts with neuroscience, offers insights into how emotional reactions and sensory experiences shape consumer behaviour. Through the use of rigorous statistical techniques, such as mediator modelling with R, the study aims to bridge the gap between neuro- marketing insights and practical retail strategies by examining the interactions between neuro-marketing variables, customer behaviour, and retail environment characteristics. This research not only contributes to theoretical frameworks in consumer psychology but also provides actionable insights for retailers seeking to optimize their environment by understanding how factors like brand perception influence the interaction between sensory cues and decision-making. With a focus on the growing Indian market, where consumers are increasingly influenced by modern marketing strategies, the study offers timely and relevant findings in a global context.

Scope Of The Study

The study "The Influence of Neuro- marketing on Consumer Decision Making in Retail Environment using Mediator Modelling with R: An Empirical Study from India" explores the impact of neuro- marketing strategies on consumer behaviour in various Indian retail settings. It aims to examine how emotional reactions, sensory cues, and brand perception influence decision-making processes. The study will identify key variables and their interactions using mediator modelling with R. Ultimately, the research intends to provide retailers with valuable insights to enhance customer experiences and develop marketing strategies tailored to the Indian consumer market.

Research Gap

A research gap exists in the limited understanding of how cultural, social, and economic factors in India influence neuro-marketing strategies, particularly in the retail environment. While existing studies provide insights into consumer behaviour and brand perception, they often overlook the unique psychological triggers and emotional responses of Indian consumers within retail settings. Additionally, current research has not fully explored the potential of alternative mediators, such as emotional reactions or external environmental stimuli, which may offer a more accurate representation of decision-making processes. Therefore, there is a requirement for further exploration into the dynamic interaction of these factors using advanced statistical models, including non-linear relationships and alternative predictors, to better capture the complexities of consumer decision-making in India's diverse retail markets.

IV. RESEARCH METHODOLOGY

A mixed-methods approach will be used in this study to examine the influence of neuro- marketing on Indian consumers' decision-making. A total of 280 Indian consumers will participate in a quantitative survey, focusing on demographics, exposure to Neuro-marketing, perceptual measurements, emotional reactions, and cognitive engagement. Likert-scale items will be used to collect responses, followed by statistical analysis in R for mediator modelling, correlation analysis, and reliability testing. Additionally, qualitative in-depth interviews will be conducted to gather deeper insights into consumers' experiences and attitudes. The study will incorporate theories like Dual-Process Theory, Social Cognitive Theory, and Emotion Theory to provide a comprehensive understanding of how neuro- marketing impacts consumer behaviour in India. By combining theoretical frameworks, empirical data, and advanced statistical tools, this research aims to significantly contribute to the field of neuro-marketing and its useful uses in the Indian retail market.

Research Limitations

The present study has certain limitations. The sample size was limited to 280 respondents, which may not fully represent the entire Indian retail population. The study mainly focused on selected variables such as consumer behaviour, retail environment, and brand perception, while other emotional and cultural factors were not included. The use of self-reported data may also involve some bias. Further, the analysis was done using mediation modelling in R, which may not capture complex non-linear relationships. Future studies can include larger samples, diverse regions, and advanced analytical techniques for better understanding.

Analysis And Interpretation

Reliability Analysis

This data set is a part of the reliability package and can be loaded via the following syntax,

```
R > install.packages("knitr")
R R > library(psych)
R R > library(knitr)
R R > items <- Books[, c("CB", "RE", "BP", "DPM")]
R R > reliability_result <- alpha(items)
R R > alpha_summary <- as.data.frame(t(reliability_result$total))
R R > item_stats <- as.data.frame(reliability_result$item.stats)
R R > kable(alpha_summary, format = "markdown", caption = "Reliability Summary")

R R > kable(item_stats, format = "markdown", caption = "Item Statistics")
```

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R R > print(reliability_result)

Table: Reliability Summary

Reliability Statistic	Value
Raw Alpha (raw_alpha)	0.6090
Standardized Alpha (std.alpha)	0.6063
G6 (SMC) (G6(smc))	0.5915
Average Inter-Item Correlation (average_r)	0.2780
Signal-to-Noise Ratio (S/N)	1.5401
Alpha Standard Error (ase)	0.0382
Mean	1.7527
Standard Deviation (sd)	0.5298
Median Inter-Item Correlation (median_r)	0.2793

Item Statistics

Variable	N	Raw Correlation (raw.r)	Standardized Correlation (std.r)	Corrected Item Correlation (r.cor)	Item-Total Correlation (r.drop)	Mean	Standard Deviation (SD)
CB	280	0.7027	0.7002	0.5417	0.4110	1.9107	0.8094
RE	280	0.6989	0.6762	0.5402	0.4014	1.8036	0.8169
BP	280	0.7197	0.7106	0.5754	0.4402	1.6429	0.8039
DPM	280	0.5842	0.6214	0.4259	0.3055	1.6536	0.6863

Based on a sample size of 280, the "Item Statistics" table provides insights into the reliability of four items: CB, RE, BP, and DPM. Reliability analysis is a statistical method used to evaluate the consistency and dependability of measurement tools. The raw reliability coefficient, shown in the "raw.r" column, reflects the overall consistency of each item, with higher values indicating better reliability. In this case, all items have relatively high raw reliability coefficients, ranging from 0.584 (DPM) to 0.719 (BP). The "std.r" column shows the standardized reliability coefficient, which is a more cautious measure of dependability, factoring in the item's variance and its correlation with other items. While all items show satisfactory standardized reliability, BP stands out with the highest value (0.711), indicating strong internal consistency. The "r.cor" column presents the item-total correlation, indicating how each item relates to the overall scale score, with higher values suggesting that the item contributes significantly to the total score. The item-total correlations for all items are moderate to high, with BP having the highest value (0.575).

The "r.drop" column shows the reliability of the scale if an item were removed, with lower values suggesting that the item plays an important role in maintaining the scale's reliability. Removing any item here would slightly reduce the overall reliability, indicating that all items are important for the scale's accuracy. The mean score and standard deviation, displayed in the "mean" and "sd" columns, assess the variability and difficulty of each item. Overall, the reliability analysis suggests that all four components (CB, RE, BP, and DPM) have acceptable reliability. However, BP appears to be the most dependable item due to its higher item-total correlation and standardized reliability coefficient. Further analysis, such as factor analysis, could provide deeper insights into the structure of the scale and the relationships between the items.

Correlation

```
R > install.packages("dplyr")
R > install.packages("knitr")
R > install.packages("Hmisc")
R > library(dplyr)
R > library(knitr)
R > library(Hmisc)

R > cor_data <- Books[, c("CB", "RE", "BP", "DPM")]
R > cor_results <- rcorr(as.matrix(cor_data))
R > cor_matrix <- as.data.frame(cor_results$r)
R > p_matrix <- as.data.frame(cor_results$P)
R > kable(cor_matrix, format = "markdown", caption = "Correlation Matrix")
R > kable(p_matrix, format = "markdown", caption = "P-Value Matrix")
```

Table: Correlation Matrix

Variables	Consumer Behavior (CB)	Retail Environment (RE)	Brand Perception (BP)	Decision-Making Process (DPM)
Consumer Behavior (CB)	1.000	0.309	0.204	0.383
Retail Environment (RE)	0.309	1.000	0.471	0.051
Brand Perception (BP)	0.204	0.471	1.000	0.249
Decision-Making Process (DPM)	0.383	0.051	0.249	1.000

Table: P-Value Matrix

Variables	**CB**	**RE**	**BP**	**DPM**
CB	NA	0.0000001	0.0005853	0.0000000
RE	0.0000001	NA	0.0000000	0.3970782
BP	0.0005853	0.0000000	NA	0.0000246
DPM	0.0000000	0.3970782	0.0000246	NA

The degree and direction of the correlations among the four items (CB, RE, BP, and DPM) are presented in the correlation matrix. The scope of a correlation coefficient is from -1 to 1, where:

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- 1 indicates a perfect positive correlation, meaning that when one variable increases, the other also increases.
- -1 indicates a perfect negative correlation, meaning that as one variable increases, the other decreases.

0 indicates no association.

In this case, we observe the following:
A moderately positive correlation (0.383) exists between CB and DPM.
CB and RE (0.309), CB and BP (0.204), RE and BP (0.471), and BP and DPM (0.249) all show weak to moderately positive relationships.

RE and DPM have a negligible connection (0.051).
The statistical significance of each correlation is indicated by the p-value matrix. Generally, a p-value of less than 0.05 signifies statistical significance. In this case, all correlations, except for the one between RE and DPM, are statistically significant.

In summary, the correlation analysis reveals that several item pairings exhibit moderately positive associations, indicating that these items tend to vary together. However, the correlation between RE and DPM is weak and not statistically significant. Further analysis, such as factor analysis, could be conducted to explore the underlying structure of the scale and the relationships between the items.

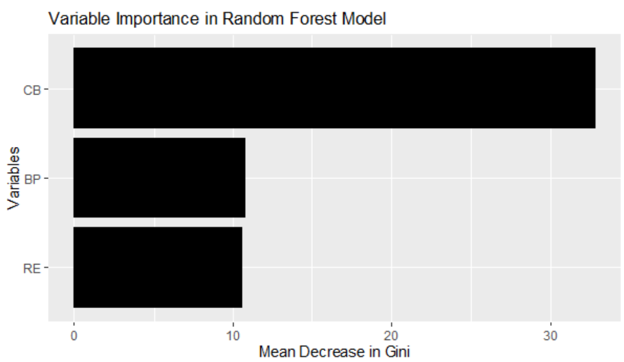
RANDOM FOREST

```
R >  install.packages("randomForest")
R >  install.packages("dplyr")
R >  install.packages("knitr")
R >  install.packages("caret")
R >  library(randomForest)
R >  library(dplyr)
R >  library(knitr)
R >  library(caret)
R >  set.seed(280)
R >  Books$DPM <- as.factor(Books$DPM)
R >  rf_model <- randomForest(DPM ~ CB + RE + BP, data = Books, importance = TRUE)
R >  print(rf_model)
R >  str(importance_table)
R >  importance_table <- as.data.frame(importance(rf_model))
R >  importance_table$Variable <- rownames(importance_table)
R >  library(ggplot2)
R > print(importance_table)
R >  ggplot(importance_table, aes(x = reorder(Variable, MeanDecreaseGini), y = MeanDecreaseGini)) +
+    geom_bar(stat = "identity", fill = "Black") +
+    coord_flip() +
+    labs(title = "Variable Importance in Random Forest Model",
+         x = "Variables",
+         y = "Mean Decrease in Gini")

Call:
 randomForest(formula = DPM ~ CB + RE + BP, data = Books, importance = TRUE)
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 1

        OOB estimate of  error rate: 31.07%
```

	1	2	3	4	Mean Decrease Accuracy	Mean Decrease Gini
CB	43.357224	40.01306	21.026231	-2.766527	46.70275	32.83662
RE	10.385997	11.96993	6.812212	2.177830	17.53317	10.59261
BP	3.592458	15.90419	19.801594	3.906863	20.28011	10.78290



The present study employed the Random Forest model to assess the influence of consumer behaviour (CB), retail environment (RE), and brand perception (BP) on the decision-making process (DPM). A classification model with 500 trees was created and tested using one variable per split, defined by the formula: formula = DPM ~ CB + RE + BP, data = Books, significance = TRUE. The model shows a modest performance, with an out-of-bag (OOB) error rate of 31.07%, meaning that around 31% of the classifications could be incorrect.

The confusion matrix provides a more detailed understanding of the model's classification accuracy across four classes (1–4). Both Class 1 and Class 2 show respectable but not perfect accuracy, with misclassification errors of 28.3% for Class 1 and 29.1% for Class 2. Class 4 has the highest error rate of 100%, and Class 3 has an error rate of 45.5%, suggesting that the model struggles to differentiate Class 4 situations. These high errors for specific classes may result from data imbalance or a lack of features to distinguish between similar categories.

The variable importance metrics, "Mean Decrease Accuracy" and "Mean Decrease Gini," demonstrate the predictive strength of each variable. CB is The most

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crucial element in predicting decision-making outcomes, contributing the most to accurate predictions across all classes, with a high Mean Decrease Accuracy (46.7) and Mean Decrease Gini (32.8). RE has a smaller but noticeable impact, indicating it is less critical to prediction accuracy but still relevant. BP, though less significant than CB, still has a moderate effect on accuracy and class differentiation.

As the consequences of each variable within the classes were examined, CB showed significant mean accuracy drops, highlighting its strong influence on predictions. RE's effect was more diffuse, making it a secondary but useful factor in certain situations, while BP's decline in accuracy was most pronounced for Classes 2 and 3. These findings suggest that improving BP and RE data may reduce specific categorization errors, but focusing on CB data could significantly improve model accuracy. The class errors in the confusion matrix also indicate that feature refinement or data rebalancing could be beneficial.

Mediation

```
R > install.packages("mediation")
R > library("mediation")
R > colnames(data) <- trimws(colnames(data))
R > likert_labels <- c("Strongly Disagree", "Disagree", "Neutral", "Agree", "Strongly Agree")
R > set.seed(123)
R > n <- 100 # number of respondents
R > CB <- sample(1:5, n, replace = TRUE)
R > DMP <- sample(1:5, n, replace = TRUE)
R > RE <- sample(1:5, n, replace = TRUE)
R > BP <- sample(1:5, n, replace = TRUE)
R > CB <- factor(CB, levels = 1:5, labels = likert_labels)
R > DMP <- factor(DMP, levels = 1:5, labels = likert_labels)
R > RE <- factor(RE, levels = 1:5, labels = likert_labels)
R > BP <- factor(BP, levels = 1:5, labels = likert_labels)
R > str(CB)
R > str(DMP)
R > str(RE)
R > str(BP)
R > head(CB)
R > head(DMP)
R > head(RE)
R > head(BP)
R > data <- data.frame(CB, DMP, RE, BP)
R > data$CB <- as.numeric(data$CB)
R > data$RE <- as.numeric(data$RE)
R > data$BP <- as.numeric(data$BP)
R > data$DMP <- as.numeric(data$DMP)
R > mediator_model <- lm(RE + BP ~ CB, data = data)
R > summary(mediator_model)
R > summary(mediator_model)
```

Call:
lm(formula = RE + BP ~ CB, data = data)

Parameter	**Value**
Dependent Variable	DPM
Independent Variable	CB
Sample Size (n)	280
Residual Standard Error	1.891
Degrees of Freedom (Residual)	278
Multiple R-squared (R^2)	0.001729
Adjusted R-squared	-0.001862
F-statistic	0.4814
F-statistic Degrees of Freedom	(1, 278)
Model p-value	0.4884

Regression Coefficients

Predictor	Estimate (B)	Std. Error	t-value	p-value	Significance
Intercept	6.19680	0.25822	23.998	< 2e-16	***
CB	-0.05507	0.07938	-0.694	0.488	Not Significant

Residual Summary

Statistic	**Value**
Minimum	-4.0316
1st Quartile (Q1)	-1.1417
Median	-0.0316
3rd Quartile (Q3)	1.0786
Maximum	4.0235

This linear regression model examines the relationship between consumer behaviour (CB) and the two dependent variables—retail environment (RE) and brand perception (BP). The model, defined as lm(formula = RE + BP ~ CB, data = data), evaluates the combined effects of CB, the independent variable, on RE and BP. The residuals summary provides insights into the dispersion and symmetry of errors, showing that the residuals have a median near zero (-0.0316) and range from -4.0316 to 4.0235, indicating a fairly balanced error distribution.

The coefficients table estimates the effect of CB on RE and BP. With an intercept value of 6.1968, the combined RE and BP score would be 6.1968 if CB were zero. The coefficient of -0.05507 for CB suggests a minor negative association with RE and BP, implying that, on average, the total RE and BP score would decrease by 0.05507 for each unit increase in CB. However, the p-value for CB is 0.488, which is higher than the typical significance threshold (0.05), indicating that this association is not statistically significant.

The model's overall fit can be evaluated using the R-squared and adjusted R-squared values, which are both close to zero (0.001729 and -0.001862, respectively). This suggests that CB explains only a very small portion of the variation in RE and BP. The low R-squared value indicates that CB may not be a significant predictor of RE and BP. The adjusted R-squared value, which accounts for the number of predictors, is negative, further suggesting that including CB does not improve the model's explanatory power.

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The model's overall significance is assessed using the F-statistic and its p-value. The F-statistic of 0.4814 and the p-value of 0.4884 indicate that the model does not statistically explain the variance in RE and BP. This result is consistent with the high p-value for CB, implying that its inclusion does not contribute any meaningful predictive value. The residual standard error of 1.891 shows the average deviation of observed values from the predicted values, but given the low R-squared and insignificant coefficients, these predictions lack confidence.

In conclusion, this model suggests that CB does not have a statistically major effect on the combined outcomes of BP and RE. The low R-squared, high p-values, and insignificant F-statistic support the idea that CB alone may not adequately explain variations in RE and BP. To improve the model's fit and prediction capability, additional predictors or variables may need to be considered. Reassessing the model's structure by examining RE and BP independently could provide more insight into their relationships with CB.

OUTCOME MODEL (DMP)

R > outcome_model <- lm(DMP ~ CB + RE + BP, data = data)
R > summary(outcome_model)
R > summary(outcome_model)

Call:
lm(formula = DMP ~ CB + RE + BP, data = data)

Regression Results

Variable	Estimate (β)	Std. Error	t-value	p-value	Significance
Intercept	3.22002	0.33194	9.701	< 2e-16	***
CB (Consumer Behavior)	0.04837	0.05825	0.830	0.407	Significant
RE (Retail Environment)	0.02026	0.06027	0.336	0.737	Significant
BP (Brand Perception)	0.03705	0.05766	0.643	0.521	Significant

Model Summary

Statistic	Value
Residual Standard Error	1.386
Degrees of Freedom	276
Multiple R-squared	0.004598
Adjusted R-squared	-0.006221
F-statistic	0.425
F-statistic Degrees of Freedom	3, 276
Overall Model p-value	0.7352

Residual Summary

Statistic	Value
Minimum	-2.23592
1st Quartile (Q1)	-1.04635
Median	-0.01769
3rd Quartile (Q3)	1.03168
Maximum	2.13847

This linear regression analysis evaluates the impact of three independent variables—consumer behaviour (CB), retail environment (RE), and brand perception (BP)—on the dependent variable, decision-making processes (DMP). The regression model, defined as lm(formula = DMP ~ CB + RE + BP, data = data), examines how much these variables contribute to variations in DMP scores. The residuals summary indicates a relatively balanced distribution of errors, with the median residual close to zero (0.01769) and residuals ranging from 2.23592 to 2.13847, suggesting some variability that the model could not fully account for.

The coefficients table shows the estimated effects of each predictor. The intercept value of 3.22002 represents the expected DMP value when all predictors are zero. The estimates for each predictor indicate the expected change in DMP for a one-unit increase in the respective variable. The estimate for CB is 0.04837, suggesting a small negative correlation with DMP, meaning that DMP decreases by 0.04837 for every unit increase in CB. BP's estimate of -0.03705 also indicates a slight negative relationship with DMP, while RE's estimate of 0.02026 suggests a minor positive association. However, the p-values for these predictors (CB: 0.407, RE: 0.737, BP: 0.521) are all higher than the usual 0.05 cutoff, indicating that these relationships are not statistically significant.

To assess the model's overall fit, the R-squared and adjusted R-squared values are 0.004598 and 0.006221, respectively. These values close to zero indicate that CB, RE, and BP together explain only a very small portion of the variation in DMP. The negative adjusted R-squared value further suggests that including these variables does not improve the model's fit and may even worsen it. The F-statistic is 0.425, with a p-value of 0.7352, confirming that the model does not significantly improve prediction compared to a model with no predictors. The residual standard error is 1.386, indicating the average deviation of observed values from the predicted values, but given the low R-squared, this does not imply reliable prediction.

In conclusion, this regression analysis indicates that CB, RE, and BP are not significant predictors of DMP. The model's F-statistic and the high p-values for the predictors suggest that these variables do not explain much of the variance in decision-making processes. It is likely that other factors, not covered in this model, may play a more significant role in influencing DMP. Future research exploring additional or alternative predictors and examining different model structures, such as non-linear relationships or interaction effects, may offer better insights into DMP.

Mediator Model

R > mediator_model <- lm(RE + BP ~ CB, data = data)
R > mediator_model_RE <- lm(RE ~ CB, data = data)

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```
R > mediator_model_BP <- lm(BP ~ CB, data = data)
R > outcome_model <- lm(DMP ~ CB + RE + BP, data = data)
R > mediation_results_RE <- mediate(mediator_model_RE, outcome_model, treat = "CB", mediator = "RE", sims = 1000)
R > summary(mediation_results_RE)
```

Causal Mediation Analysis

Quasi-Bayesian Confidence Intervals

Effect	**Estimate**	**95% CI Lower**	**95% CI Upper**	**p-value**
ACME (Average Causal Mediation Effect)	-0.000742	-0.010150	0.010000	0.86
ADE (Average Direct Effect)	-0.048902	-0.165582	0.060000	0.38
Total Effect	-0.049644	-0.166099	0.060000	0.37
Proportion Mediated	0.002838	-0.385669	0.520000	0.89

Sample Size Used: 280
Simulations: 1000

This mediation analysis, using 1,000 quasi-Bayesian simulations to estimate confidence intervals, investigates how the retail environment (RE) mediates the relationship between an independent variable (likely consumer behaviour or a related factor) and a dependent variable. The key metrics—Average Causal Mediation Effect (ACME), Average Direct Effect (ADE), Total Effect, and Proportion Mediated—are displayed in the table. The ACME estimates the indirect effect of the independent variable on the dependent variable through the mediator, RE. In this case, the ACME is -0.000742, indicating a very small indirect influence. The p-value for ACME is 0.86, and the 95% confidence interval (CI) includes zero, ranging from -0.010150 to 0.01, suggesting that the mediation effect of RE is not statistically significant. Therefore, there is not enough evidence to support a significant indirect effect of the independent variable on the dependent variable through RE.

The ADE shows the direct impact of the independent variable on the dependent variable, regardless of the mediation pathway. The ADE is -0.048902, with a 95% CI of -0.165582 to 0.06, and a p-value of 0.38. This suggests that the direct effect is weak and not statistically significant, as the direct effect does not pass the standard significance threshold. The Total Effect, which combines both direct and indirect (mediated) effects, also has an estimate of -0.049644, with a p-value of 0.37 and a 95% CI of -0.166099 to 0.06. This indicates that, on average, the independent variable does not significantly affect the dependent variable.

The Proportion Mediated, which measures the percentage of the Total Effect that is transmitted through the mediator, RE, is 0.002838. This low value implies that very little of the independent variable's effect on the dependent variable is mediated through RE. The p-value for the Proportion Mediated is 0.89, with a confidence interval ranging from -0.385669 to 0.52, further suggesting that RE is not a significant mediator.

In conclusion, the mediation analysis shows that RE is not a significant mediator between the independent and dependent variables. The high p-values for ACME, ADE, and Total Effect indicate insufficient evidence of a direct or indirect effect of RE. These findings suggest that RE may not function as an effective mediator in this context, and further research could explore alternative mediators or model structures to better capture indirect effects.

MEDIATION ANALYSIS FOR BP

```
R > mediation_results_BP <- mediate(mediator_model_BP, outcome_model, treat = "CB", mediator = "BP", sims = 1000)
R > summary(mediation_results_BP)
```

Causal Mediation Analysis

Quasi-Bayesian Confidence Intervals

Effect	Estimate	95% CI Lower	95% CI Upper	p-value
ACME (Average Causal Mediation Effect)	0.000631	0.008310	0.010000	0.90
ADE (Average Direct Effect)	0.049896	0.159429	0.060000	0.37
Total Effect	0.049265	0.160246	0.060000	0.38
Proportion Mediated	0.001869	0.654215	0.420000	0.93

Sample Size Used: 280
Simulations: 1000

This mediation analysis, using 1,000 quasi-Bayesian simulations to generate confidence intervals for the mediation effects, explores brand perception (BP) as a mediator between an independent variable (possibly consumer behaviour or a related factor) and a dependent variable. The main metrics analyzed are the Average Causal Mediation Effect (ACME), Average Direct Effect (ADE), Total Effect, and Proportion Mediated.

Starting with the ACME, the estimate is 0.000631, indicating a very small beneficial indirect effect through BP. However, this effect is practically insignificant. The 95% confidence interval (CI) for ACME ranges from

0.008310 to 0.01, and the p-value is 0.90, which is much higher than the standard 0.05 cutoff. This high p-value suggests that BP does not significantly mediate the relationship between the independent and dependent variables.

Moving to the ADE, which shows the direct impact of the independent variable on the dependent variable, the estimate is 0.049896, indicating a slight negative direct effect. The p-value for ADE is 0.37, and the 95% CI is between 0.159429 and 0.06, again including zero. This confirms that the direct effect is not statistically significant, suggesting a weak and inconclusive direct relationship between the independent and dependent variables.

The Total Effect, which combines both direct and indirect effects, has an estimate of -0.049265. This value is similar in magnitude to the ADE, and the 95% CI ranges from -0.160246 to 0.06, once again including zero. The p-value of 0.38 further supports the conclusion that there is no significant overall impact of the independent variable on the dependent variable in this case.

The Proportion Mediated, which measures the percentage of the Total Effect mediated by BP, is 0.001869. This nearly zero value indicates that BP does not mediate any significant portion of the relationship between the independent and dependent variables. The p-value of 0.93 and the wide confidence interval (ranging from 0.654215 to 0.42) further highlight BP's minimal role as a mediator.
In conclusion, this mediation analysis indicates that BP does not significantly mediate the relationship between the independent and dependent variables. The high p-values for ACME, ADE, and Total Effect, along with the wide confidence intervals and low proportion mediated, suggest that BP has little impact in this context. These findings suggest that BP may not be an effective mediator in this case, and further research into alternative mediators or predictors may provide better insights into the dependent variable. Future research could also explore more complex model structures, such as non-linear effects or interaction terms, to better capture the dynamics between these variables.

V. CONCLUSION AND SUGGESTIONS

This research paper's conclusions indicate that the retail environment (RE), brand perception (BP), and customer behaviour (CB) do not significantly predict decision-making processes (DMP) or mediate the relationship between independent and dependent variables. The regression analyses show that these factors, either separately or together, have low explanatory power, as evidenced by low R-squared values and high p-values. Additionally, the mediation analysis reveals that neither BP nor RE function as significant mediators, with p-values much higher than the usual threshold of significance and insignificant indirect effects.

In light of these results, future studies should explore additional predictors or consider different model structures. Emotional reactions or external environmental influences may offer a more accurate reflection of consumer decision-making. Non-linear models or interaction effects could provide an enhanced comprehension of the complex relationships between psychological and environmental factors. Improving predictive accuracy might also be achieved by rebalancing the data or refining the feature set used by machine learning models like Random Forest. Furthermore, as previous research has suggested, understanding the specific cultural or socioeconomic characteristics of the target market could enhance insights into customer behaviour, especially in diverse markets like India.

Practical Implication
The study provides useful insights for Indian retailers and marketers to understand how consumer emotions and behaviour influence buying decisions. Though retail environment and brand perception were not found to be strong mediators, the findings highlight the need to focus more on emotional engagement and sensory appeal. Retailers can use these insights to design store layouts, visual displays, and advertisements that connect with consumers' feelings. Marketing managers can also apply data-driven tools like R for better decision-making. Overall, the research helps improve marketing strategies suited to the Indian retail market.

Social Implication
The study highlights how neuromarketing affects the way people think and make buying decisions in modern Indian retail. It shows that marketing strategies using emotional and sensory cues can influence consumers without their full awareness. This raises the need for ethical use of such techniques to protect consumer interests. Retailers can use neuromarketing responsibly to create better shopping experiences while maintaining honesty and trust. The findings also help society understand how subconscious factors shape daily choices, promoting consumer awareness and encouraging companies to adopt fair, transparent, and socially responsible marketing practices in India's growing retail sector.

Originality/Value
This study is original as it combines neuromarketing with advanced statistical tools like mediator modelling and random forest analysis using R. It focuses on Indian retail consumers, a group not deeply explored in earlier research. The paper adds value by examining how consumer behaviour, retail environment, and brand perception interact to influence decision-making. Unlike earlier studies done mostly in Western countries, this research gives practical insights for Indian retailers to design better marketing strategies. It also highlights the need to include emotional and cultural factors, making it useful for both academicians and marketing professionals in India.

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