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# Predicting Annual Customer Spending in E-commerce: A Comparative Analysis of Mobile App and Website Interaction Metrics

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## Abstract

In the competitive world of e-commerce, companies must continuously optimize their digital platforms to increase customer engagement and drive revenue. This project focuses on predicting annual customer income for an e-commerce company based in London, which operates both online clothing sales and in-store personal stylist consultations. The company aims to determine whether to focus on improving its mobile app or website to maximize customer spending. By analyzing user behavior—such as time spent on the mobile app, time spent on the website, average in-store session length, and membership duration—this study identifies the factors that most significantly impact customer spending.

To achieve this, three machine learning approaches were employed: **Recurrent Neural Networks (RNN)**, **Regression Analysis**, and **Decision Tree Regression (DT Regression)**. RNNs were used to capture sequential patterns in user behavior, while Regression Analysis provided a baseline for understanding linear relationships between the features and the target variable. However, **Decision Tree Regression** outperformed both models by effectively capturing non-linear relationships and offering high interpretability, making it the most accurate method for predicting annual income.

The results show that **time spent on the mobile app** is the strongest predictor of customer spending, followed by **membership length**. Time spent on the website, while still significant, had a weaker influence on annual income. Additionally, in-store session length had a relatively smaller impact, highlighting the greater importance of digital interactions in influencing customer purchases. These insights lead to a clear recommendation: the company should prioritize improving its mobile app experience to drive higher customer engagement and revenue.

Overall, this study provides valuable, data-driven guidance for the company's strategic decision-making, helping them allocate resources effectively between their mobile app, website, and in-store services.

## 1. Introduction

### Background and Motivation

In the dynamic world of e-commerce, companies are continually striving to optimize customer experience and increase revenue by leveraging both digital platforms and in-store services. For businesses that combine online retail with personalized in-store services, understanding the factors that drive customer spending is crucial for strategic decision-making. The company in this study, based in London, operates a unique hybrid model by offering both online clothing sales and in-store personal stylist consultations. Customers have the option to visit the store, receive fashion advice from a personal stylist, and then purchase items online via the company's mobile app or website.

In today's digital-first environment, customer behavior on digital platforms plays a significant role in influencing their purchasing decisions. As mobile devices become increasingly prevalent, many e-commerce businesses face the question of whether to focus their efforts on improving the mobile app experience or the website. The company in this study is particularly interested in understanding which platform—mobile app or website—has a greater influence on customer spending. This decision could significantly impact where the company invests resources to optimize customer engagement and drive revenue.

This research project aims to predict annual customer spending based on user behavior, including metrics such as **average in-store session length**, **time spent on the mobile app**, **time spent on the website**, and **membership length**. By identifying the key drivers of customer spending, the company can tailor its efforts towards the most impactful areas, helping them enhance customer satisfaction and increase profitability.

**Problem Statement and Objective**

The primary goal of this study is to determine which factors most significantly influence customer annual income, particularly in terms of digital behavior, and to use this information to predict annual spending. The core research question is:

*Which digital platform—mobile app or website—contributes more to predicting annual customer spending, and how can the company leverage this insight to improve business outcomes?*

To answer this question, the study utilizes various machine learning models to analyze customer behavior and predict annual spending. Specifically, this research focuses on evaluating three types of predictive models: **Recurrent Neural Networks (RNN)**, **Regression Analysis**, and **Decision Tree Regression (DT Regression)**. These models are used to predict customer annual income based on several input features, including time spent on the app, time spent on the website, average session length, and membership duration.

After training and evaluating the models, **Decision Tree Regression** emerged as the most accurate model in predicting customer spending, providing actionable insights into which factors contribute most to annual income. The results of this study offer clear guidance on whether the company should prioritize improving its mobile app experience or its website to maximize customer engagement and spending.

**Importance of Predicting Customer Spending in E-commerce**

E-commerce companies thrive on understanding their customers' behavior and identifying patterns that lead to increased sales. Predicting customer spending helps companies:

**Personalize marketing strategies**: Knowing which customers are likely to spend more can help in tailoring marketing efforts, offering personalized deals, and improving customer retention.

**Optimize resource allocation**: By identifying which digital platforms (mobile app or website) lead to higher spending, companies can allocate resources more efficiently.

**Improve customer satisfaction**: By focusing on improving the platforms and services that customers use the most, companies can provide a better overall shopping experience.
**Increase profitability**: Accurate predictions of customer spending allow companies to make data-driven decisions that directly impact sales and revenue.
In this study, the company's goal is to determine whether to invest in its **mobile app** or its **website** based on which platform contributes more to yearly customer spending. Through data analysis and machine learning techniques, the study provides evidence-based recommendations for the company to prioritize its digital strategy.

**Overview of Methods Used**
In this research, we used three different machine learning approaches—**Recurrent Neural Networks (RNN)**, **Regression Analysis**, and **Decision Tree Regression (DT Regression)**—to predict annual customer income based on their behavior.
**Recurrent Neural Networks (RNN)**:
**RNNs** are widely used for time-series prediction tasks due to their ability to process sequential data. In this study, RNNs were employed to analyze user behavior over time, particularly focusing on time spent on the app and website. The model aimed to capture any patterns in user activity that could contribute to predicting annual spending.
**Challenges**: While RNNs are powerful for time-dependent data, the model struggled with non-sequential features like membership length and average session length, leading to lower accuracy compared to other models.
**Regression Analysis**:
**Regression Analysis** is a statistical method used to model the relationship between a dependent variable (annual income) and one or more independent variables (features like time spent on app, time on website, etc.). Linear Regression, in particular, was used as a baseline model to understand the linear relationships between user behavior and spending.
**Limitations**: Although Linear Regression provided a clear understanding of the general trends in the data, it was unable to capture the complex, non-linear relationships present in the dataset. The accuracy of the model was lower compared to more sophisticated algorithms.
**Decision Tree Regression (DT Regression)**:
**Decision Tree Regression** emerged as the most effective model for predicting annual customer income. This model splits the dataset into smaller subsets based on feature values, creating a tree-like structure where each internal node represents a decision based on a feature, and each leaf node represents a predicted value (annual income).
**Why Decision Tree Regression**: DT Regression was chosen because it can handle non-linear relationships, does not require extensive data preprocessing (such as scaling or normalization), and is easy to interpret. Additionally, Decision Trees are capable of modeling interactions between variables like time spent on the app and website, which are critical for predicting customer income.
**Higher Accuracy**: Among all the models tested, Decision Tree Regression demonstrated the highest accuracy in predicting customer spending, with a significantly lower Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The tree's ability to capture non-linear patterns in the data, combined with its interpretability, made it the best-suited model for this study.

**Key Findings**
The analysis of customer behavior data led to several key insights:

**Time spent on the mobile app**: This feature emerged as the strongest predictor of annual income. Customers who spend more time on the app tend to have higher yearly spending, suggesting that improving the mobile app experience could lead to increased customer engagement and revenue.
**Time spent on the website**: While still significant, time spent on the website had a weaker correlation with annual income compared to time spent on the app. This suggests that customers prefer the app for shopping, and the website may serve more as a research tool.
**Membership length**: Customers with longer memberships were found to have higher annual spending, indicating the importance of building long-term relationships with customers.
**In-store session length**: Surprisingly, the average session length of in-store consultations had a lower-than-expected impact on annual spending, suggesting that digital interactions play a more critical role in influencing customer purchases.

**Conclusion of the Introduction**

In conclusion, this study provides a comprehensive analysis of customer behavior in an e-commerce setting, using a combination of **Recurrent Neural Networks (RNN)**, **Regression Analysis**, and **Decision Tree Regression** to predict annual spending. **Decision Tree Regression** was found to be the most accurate model, offering key insights into customer preferences and platform usage. The findings suggest that the company should prioritize improving its mobile app experience to drive higher customer engagement and increase annual income.
This research offers a data-driven foundation for the company to make strategic decisions about platform investment, helping them allocate resources effectively to maximize profitability.

# Literature Review

### 1. E-commerce and Customer Engagement

The rapid growth of e-commerce has significantly reshaped the retail landscape, introducing new dynamics in consumer behavior and engagement strategies. E-commerce refers to the buying and selling of goods or services through electronic platforms, and it encompasses a wide range of activities, including online shopping, electronic payments, and online order fulfillment. According to Verhoef et al. (2015), effective customer engagement is pivotal for online retailers aiming to cultivate loyalty and drive repeat purchases. Customer engagement can be defined as the emotional and psychological connection that a customer forms with a brand, influenced by multiple touchpoints throughout the customer journey.
Engagement strategies often extend beyond the digital realm to include in-store experiences, which are crucial in establishing customer relationships. For instance, when customers interact with a brand in physical stores, their experiences significantly shape their perceptions and intentions to engage online later. Lemon and Verhoef (2016) emphasize the importance of a seamless integration between online and offline experiences, asserting that positive in-store interactions can lead to increased online spending. This connection highlights the need for businesses to understand and optimize the entire customer journey, ensuring that each interaction enhances overall engagement and satisfaction.
In the context of fashion retail, where style and personalization are paramount, the integration of personalized services—such as in-store styling consultations—can profoundly influence online shopping behavior. Customers who receive tailored advice from knowledgeable stylists are more likely to feel empowered and confident in their purchasing decisions. This empowerment not only increases the likelihood of online purchases but also fosters brand loyalty, as consumers appreciate and remember the personal touch associated with their shopping experience.

**2. Impact of In-Store Experiences on Online Spending**

Research indicates that in-store experiences have a direct correlation with online spending patterns. Kumar and Pansari (2016) demonstrate that customers who participate in personalized, face-to-face styling sessions exhibit higher spending when they shop online. This phenomenon can be attributed to several factors. Firstly, in-store interactions provide customers with immediate feedback and reassurance about their choices, enhancing their confidence in the products they decide to purchase. Secondly, personalized sessions create a sense of community and belonging among customers, which can lead to increased brand loyalty and advocacy.

Furthermore, the role of social influence cannot be underestimated in the context of in-store styling. As noted by Cialdini (2009), social proof—where individuals look to others to guide their decisions—plays a significant role in consumer behavior. Customers who see others engaging positively with stylists may be more likely to trust the brand and its offerings. In turn, this trust translates into increased online engagement and spending as customers feel assured of the value they are receiving from the brand.

In addition to enhancing confidence, personalized in-store experiences can lead to a greater emotional investment in the brand. Emotional connection is a powerful driver of consumer behaviour, influencing not only purchase decisions but also long-term brand loyalty. Research conducted by Thomson et al. (2005) indicates that brands that forge strong emotional connections with customers are more likely to see higher levels of engagement and spending. Therefore, e-commerce strategies should focus on leveraging in-store experiences to create lasting emotional ties, ultimately driving online purchasing behaviour.

3. Mobile vs. Website User Experience

The decision to prioritize mobile app development or website enhancement is a critical consideration for e-commerce companies. With the increasing prevalence of smartphones, consumers are spending more time on mobile applications than ever before. Xu et al. (2016) found that mobile apps often offer a superior user experience compared to traditional websites. This superiority is attributed to several key factors, including personalized features, ease of use, and quicker access to information.

Mobile applications enable brands to provide a more personalized experience by utilizing data analytics to tailor content and recommendations to individual users. Features such as push notifications allow brands to engage customers with timely updates and offers, fostering a sense of urgency and encouraging immediate purchases. For instance, a customer who has recently engaged with a stylist in-store may receive a push notification about a new clothing line that complements their previous selections, prompting them to make a purchase via the app.

Conversely, while mobile apps excel in personalization, websites remain vital for providing comprehensive product information and comparison tools. Wang and Benbasat (2007) argue that websites are particularly effective for customers seeking detailed information about products, including specifications, customer reviews, and pricing comparisons. This level of detail is crucial for informed purchasing decisions, especially in fashion retail, where consumers often desire to understand the quality and fit of clothing items before making a commitment.

Moreover, the accessibility of websites on various devices allows consumers to shop from any platform, whether on a desktop or mobile device. This multi-device accessibility is crucial in today's digital landscape, where customers expect a seamless shopping experience across channels. Understanding the distinct advantages of both platforms is essential for businesses as they strategize their e-commerce efforts. As a result, companies must consider their target audience's preferences, the nature of their products, and their overall brand strategy when determining where to focus their resources.

**4. Factors Influencing Annual Spending in E-commerce**

Several key factors influence customer spending in e-commerce, and understanding these factors is critical for developing effective strategies. Homburg et al. (2014) highlight several critical variables, including session length, time spent on digital platforms, length of membership, and overall engagement.

**Session Length and Customer Spending**
The average length of in-store sessions with stylists can significantly influence online spending. Longer, more personalized interactions allow customers to explore various styles and options, leading to more informed online purchases. This connection suggests that in-store experiences should be designed to maximize engagement and provide thorough assistance to customers.

**Time on App vs. Website**
The amount of time customers spend engaging with the app or website serves as an essential metric of customer interest and engagement. Increased time spent typically correlates with higher spending, reflecting a customer's growing relationship with the brand. A study by Lemon et al. (2020) supports this notion, indicating that users who invest more time in a mobile app often exhibit higher purchase rates compared to those primarily engaging through a website.

**Length of Membership**
The duration of customer membership is another vital predictor of spending behavior. Long-term customers are more likely to exhibit loyalty and trust in the brand, leading to increased spending over time. Research by Kahn et al. (2016) indicates that customers with longer memberships are more inclined to make larger purchases due to their established relationships with the brand and familiarity with its offerings.

Additionally, engagement metrics, such as the frequency of app usage or website visits, can provide insights into customer loyalty and preferences. Customers who regularly interact with the brand's platforms are likely to develop a deeper emotional connection, which can result in higher annual spending. Therefore, understanding these factors is essential for businesses aiming to refine their e-commerce strategies.

## 5. Predictive Modeling in E-commerce

The utilization of predictive analytics in e-commerce has emerged as a powerful tool for understanding customer behavior and informing strategic decisions. Shmueli and Koppius (2011) emphasize that predictive models can effectively identify the key factors driving customer spending and engagement. Techniques such as regression analysis, machine learning, and data mining enable businesses to analyze customer data, uncover trends, and make informed predictions about future behaviour.

In the context of the current project, leveraging the numerical columns from the company's e-commerce dataset—such as average session length, time on the app, time on the website, length of membership, and yearly amount spent—will be critical for developing a robust predictive model. This model can help identify the variables most strongly associated with annual spending and enable the company to optimize its strategies accordingly.

Furthermore, predictive analytics can facilitate targeted marketing efforts by identifying high-value customer segments. For example, if the model reveals that customers who engage frequently with in-store stylists are likely to spend significantly more online, the company can develop targeted campaigns to encourage these customers to return for additional styling sessions, thereby enhancing their overall shopping experience and increasing revenue.

## 6. Conclusion

The literature underscores the intricate relationship between in-store experiences and online spending behaviour, highlighting the importance of a cohesive multi-channel approach in e-commerce. By understanding the factors that contribute to annual income predictions, businesses can make data-driven decisions to optimize their strategies for enhancing customer engagement and satisfaction. For the clothing company in London, the strategic focus on improving customer interactions—whether through a mobile app or website—will be essential for maximizing revenue potential and fostering long-term customer loyalty. Ultimately, the decision to prioritize the mobile app or website experience should be informed by an in-depth analysis of customer behavior, preferences, and engagement patterns. By leveraging insights from predictive modeling and focusing on creating personalized experiences, the company can effectively navigate the complexities of the modern e-commerce landscape and achieve sustainable growth.

# 3. Architecture and Design

The architecture and design of this project were crafted to systematically address the problem of predicting customer annual income based on their behavior on digital platforms and in-store sessions. A structured approach was employed, encompassing data collection, preprocessing, feature engineering, model selection, and evaluation.

### 3.1 Design Strategy

The design strategy employed in this project is fundamentally centered around the integration of multiple machine learning models to leverage their strengths while mitigating their weaknesses. The strategy consists of the following key elements:

**Data Collection and Preprocessing:** The initial step involves gathering a diverse dataset that includes various user behavior parameters, such as clickstream data, time spent on the app and website, user demographics, and purchase history. The preprocessing stage ensures the dataset is cleaned, with missing values handled and irrelevant features removed. This step is crucial to prepare the data for effective analysis and modeling.

**Feature Engineering:** This step focuses on creating new informative features from the raw dataset. Temporal features, such as the time spent on the platform and frequency of visits, are generated to capture seasonal and behavioral patterns affecting e-commerce spending. Additionally, encoding categorical variables and scaling numerical features ensures they contribute effectively to model training.

**Model Selection and Hybridization:** The design strategy emphasizes a hybrid modeling approach. By integrating different algorithms, specifically the Random Forest Regressor, Gradient Boosting Regressor, and a Stacked Regressor, the model aims to achieve superior predictive performance. Each model brings unique capabilities, allowing for enhanced adaptability to the underlying data distribution.

**Evaluation Metrics:** The project employs a variety of evaluation metrics—Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared ($R^2$)—to assess model performance comprehensively. These metrics provide insights into the accuracy and reliability of the predictions, guiding iterative improvements.

### 3.2 Architectural Components

The architectural framework consists of several interdependent components that work collaboratively to achieve the project's objectives. Each component plays a pivotal role in the overall system:

**Data Ingestion:** This component is responsible for importing the dataset from various sources, such as databases or CSV files. A robust data ingestion process ensures that the system can effectively handle varying data formats and sizes, laying the groundwork for subsequent analyses.

**Data Processing Pipeline:** The data processing pipeline encompasses several critical stages:

**Data Cleaning:** Removing or imputing missing values and correcting inconsistencies in the dataset to maintain data integrity.

**Transformation:** Converting data types and normalizing values to ensure consistency across features. This includes scaling numerical features to a common range and encoding categorical variables into numerical formats for model compatibility.
**Feature Extraction:** Generating new features from existing ones, such as isolating behavioral patterns from user interaction data.
**Model Training and Evaluation:** The core component of the architecture involves training the individual machine learning models and the hybrid ensemble model. This includes:
**Base Model Training:** Training each individual model (e.g., Random Forest, Gradient Boosting) separately on the training dataset.
**Stacking Model Implementation:** Combining the outputs of the base models using a meta-learner (e.g., Linear Regression) to form a unified predictive model. This stacked approach aims to capitalize on the strengths of each base model.
**Prediction System:** The prediction system utilizes the trained hybrid model to make forecasts on new, unseen data. This component integrates the predictions from the base models and produces final output values, enhancing overall accuracy.
**Visualization and Reporting:** Effective visualization tools are employed to assess model performance. Graphical representations, such as scatter plots and error distributions, provide intuitive insights into model behavior. This component also includes generating reports that summarize the findings and metrics for stakeholder presentation.

### 3.3 Parametric Analysis

Parametric analysis plays a critical role in understanding how different parameters affect model performance. Key parameters evaluated in this project include:
**Number of Estimators:** In ensemble methods like Random Forest and Gradient Boosting, the number of trees significantly influences model performance. A higher number of estimators generally improves accuracy but may increase computational overhead.
**Learning Rate:** For boosting algorithms, the learning rate determines the step size taken towards the minimum of the loss function. A smaller learning rate can yield better results but may require a larger number of estimators to converge effectively.
**Maximum Depth:** This parameter controls the maximum depth of the trees in decision tree-based models. Setting an optimal maximum depth is crucial for preventing overfitting while ensuring the model captures complex relationships in the data.
**Regularization Parameters:** Regularization techniques, such as L2 regularization, help constrain the model coefficients to prevent overfitting. The balance between model complexity and generalization is assessed by tuning these parameters.
The parameter tuning process is conducted using techniques such as grid search or randomized search, ensuring the models are optimized for the best possible performance.

### 3.4 Sensitivity and Uncertainty Analysis

**Sensitivity Analysis:** This analysis investigates how sensitive model predictions are to changes in input features. By systematically varying the values of input variables, the analysis identifies which features have the most significant impact on the model's predictions. This information is valuable for feature selection and prioritizing data collection efforts.
**Uncertainty Analysis:** Uncertainty analysis quantifies the confidence in model predictions by assessing variability across different scenarios. Techniques such as bootstrapping or Monte Carlo simulations can be employed to estimate prediction intervals and evaluate the robustness of the model's outputs. Understanding the uncertainty surrounding predictions is crucial for informed decision-making in e-commerce strategies.

### 3.5 Conclusion of Architecture and Design

The architecture and design of the project were carefully crafted to address the e-commerce company's core objective: predicting customer annual income based on their behavior across both in-store sessions and digital platforms. The design approach not only emphasized predictive accuracy but also aimed to provide interpretable and actionable insights for strategic decision-making.

Comprehensive and Scalable Architecture

The architecture of this project was designed with flexibility and scalability in mind, ensuring that it can evolve with the company's future data and business needs. At its core, the design utilized a combination of different machine learning techniques, including Recurrent Neural Networks (RNN), Regression Analysis, and Decision Tree Regression.

**Recurrent Neural Networks (RNN):**

RNNs were employed for time-series analysis, particularly for sequential features like time spent on the mobile app and time on the website. The goal was to capture patterns over time that might influence customer spending. However, RNNs struggled with non-sequential data (e.g., membership length), which limited their overall predictive accuracy in this context.

Despite these limitations, the inclusion of RNN in the architecture provided valuable insights into user behavior trends over time, such as the consistency of app usage across membership duration.

**Regression Analysis:**

Linear Regression was used as a baseline model to understand the linear relationships between various features, such as time on app, time on website, average in-store session length, and customer income. This model provided a basic understanding of how each feature contributes to predicting annual income.

However, the linear model faced limitations in capturing complex, non-linear relationships in the dataset, such as the interaction between app usage and membership length. It was determined that a more sophisticated approach was necessary to accurately capture these non-linear patterns, which led to the inclusion of Decision Tree Regression in the architecture.

**Decision Tree Regression (DT Regression):**

Decision Tree Regression emerged as the cornerstone of the model architecture due to its ability to handle both linear and non-linear relationships. Decision Trees split the dataset into smaller subsets based on feature values, enabling the model to make predictions at each decision node. This feature made it well-suited to capture complex interactions between features like time spent on the app, membership duration, and customer spending.

One of the major advantages of Decision Tree Regression is its interpretability. Each decision made by the model can be easily visualized and explained, making it easier for the company to understand which factors drive customer spending and how they relate to each other.

Moreover, the flexibility of Decision Trees allows for easy handling of mixed data types (both numerical and categorical) without the need for extensive preprocessing. This made it highly efficient in processing the company's behavioral data.

Strategic Design Considerations

The overall design of the architecture was guided by the following principles:

**Modularity:**

The project's architecture was designed to be modular, meaning that each component of the model can function independently while contributing to the overall system. This modularity ensures that future enhancements, such as the addition of new features (e.g., product browsing history, customer reviews), can be seamlessly integrated into the system without significant re-engineering. For instance, if the company collects more data related to customer behavior, it can be easily incorporated into the existing design framework to enhance predictive accuracy.

**Interpretability and Business Insights:**

A key design consideration was ensuring that the model's outputs were interpretable and provided actionable insights. Decision Tree Regression played a pivotal role in this aspect, offering clear and understandable decision paths. For instance, the company can trace why certain customers are predicted to spend more based on time spent on the app or membership length. This transparency enables the company to make informed business decisions, such as tailoring marketing strategies or deciding which platform (mobile app or website) to prioritize for development.

The model's ability to interpret and visualize relationships between features allowed the company to better understand the importance of each factor. For example, time spent on the mobile app consistently emerged as the most significant factor driving annual income, followed by membership duration.

**Evaluation and Accuracy:**

Throughout the design process, various machine learning models were evaluated using standard metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared ($R^2$). These metrics provided a quantitative measure of the model's performance and ensured that the chosen architecture was optimized for accuracy.

Decision Tree Regression outperformed both Recurrent Neural Networks (RNN) and Linear Regression models in terms of accuracy, particularly when predicting customer spending based on non-linear patterns. Its superior performance was attributed to its ability to capture the complex interactions between features, such as the correlation between time on app and membership length.

**Handling Overfitting and Model Generalization**

Overfitting is a common challenge in machine learning models, especially in Decision Trees that can grow excessively deep and model noise in the data. To address this, several strategies were employed:

Pruning: Pruning techniques were implemented to reduce the depth of the decision tree and prevent overfitting. By limiting the maximum depth and setting minimum sample requirements for splits, the model avoided capturing noise in the data, ensuring that it could generalize better to unseen data.

Cross-Validation: The model was validated using cross-validation techniques, splitting the dataset into multiple training and testing sets to assess the model's performance across different data samples. This helped in identifying the best-performing model configuration that generalized well to new data.

Feature Selection: To further reduce the risk of overfitting, feature importance scores were analyzed, and redundant or less significant features were excluded from the model. For example, in-store session length, while included initially, showed relatively low importance compared to digital metrics like time on app and membership length, and was thus deprioritized in the final model architecture.

**Business Impact and Future Scalability**

The design of the model was directly aligned with the company's strategic needs:

Prioritization of Digital Platforms: The model's outputs revealed that time spent on the mobile app was the most significant factor driving customer annual income. This insight provides clear guidance for the company to prioritize investments in improving the mobile app experience. Enhancements such as personalized recommendations, user-friendly navigation, and seamless checkout experiences on the mobile app are likely to result in increased customer spending.

Scalability for Future Needs: The architecture is designed to be scalable, allowing for future enhancements without overhauling the system. The company can easily incorporate new customer behavior data, such as product reviews, purchase history, or engagement with promotional content, into the model. This ensures that the architecture remains adaptable and continues to provide accurate insights as the company's business evolves.

**Conclusion**

In conclusion, the architecture and design of this project effectively addressed the company's goal of predicting customer annual income based on user behavior. The decision to incorporate Decision Tree Regression as the primary model proved to be highly successful due to its ability to handle non-linear relationships and offer transparent, interpretable results. The modular and scalable design ensures that the model can evolve with the company's future data needs and business goals. By providing actionable insights into customer behavior, the architecture enables the company to make informed decisions about resource allocation, particularly regarding the development of their digital platforms. The project not only meets the technical objectives but also delivers critical business value, supporting the company's growth and profitability.

### 3.5 Conclusion of Architecture and Design

The architecture and design of this project were structured to address the key business question of predicting customer annual income based on behavioral data collected from both digital platforms and in-store experiences. This design sought to not only provide accurate predictions but also deliver actionable insights for strategic decision-making, particularly for optimizing the company's mobile app and website.

Comprehensive Design Strategy

The design of the architecture followed a systematic approach to solve the business problem, ensuring flexibility, accuracy, and interpretability. The design was built to handle both numerical and categorical data, capture non-linear relationships, and offer clear business insights. Key design components included:

**Data Collection and Preprocessing:**

The dataset provided by the company contained behavioral metrics such as Time on App, Time on Website, Average In-store Session Length, and Length of Membership. These variables were used to predict Yearly Amount Spent.

The preprocessing steps included handling missing values, encoding categorical variables, and splitting the data into training and test sets. The features were not scaled, as models like Decision Tree Regression do not require feature scaling, simplifying the preprocessing pipeline.

**Feature Engineering:**

Temporal features like membership length were calculated to understand how customer loyalty impacts spending over time.

Additional interaction features, such as the interaction between time spent on the app and membership duration, were analyzed to capture deeper relationships between user behavior and spending patterns.

**Modular Design for Model Selection:**

The model selection process involved a comparison of multiple machine learning approaches. Each model was tested independently and combined in a modular fashion, ensuring flexibility and ease of testing.

**The models used included:**

Recurrent Neural Networks (RNN) for sequential analysis of time-series data (e.g., time spent on the app and website over time).

Regression Analysis (Linear Regression) to establish baseline performance and understand linear relationships between the input features and annual income.

Decision Tree Regression (DT Regression), which was selected for its ability to capture complex, non-linear relationships and offer easy interpretability.

**Model Training and Evaluation:**
The model architecture was designed to support iterative improvements in performance, with each model being trained using cross-validation to ensure robustness. Metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared ($R^2$) were used to evaluate model performance, providing quantitative measures of the prediction accuracy.
Decision Tree Regression was chosen as the final model because of its superior accuracy, flexibility in handling non-linear data, and its ability to clearly explain the contribution of each feature to the prediction outcome.

**Model Architecture and Choice of Decision Tree Regression**
**Recurrent Neural Networks (RNN):**
RNNs were included in the architecture to capture sequential dependencies in time-series data, especially focusing on time spent on the app and website over a period. However, the RNN struggled with non-sequential features like membership length, and the complexity of training an RNN did not yield significantly better results compared to other models.
While RNNs were useful for sequential data, their performance was suboptimal when the entire dataset (which contained non-temporal variables) was taken into consideration.

**Regression Analysis:**
Linear Regression served as a baseline model to assess the linear relationships between customer behavior (e.g., time on app, time on website) and annual income. While Regression Analysis provided useful insights into general trends, it failed to capture the complex interactions between the features, such as how increasing time spent on the app interacts with membership length.
Its performance was limited because the relationships between variables like time on app and customer spending were not strictly linear. Thus, a more sophisticated model was required.
**Decision Tree Regression (DT Regression):**
Decision Tree Regression emerged as the most effective model due to its ability to capture both linear and non-linear relationships without requiring extensive data preprocessing.
The tree-based architecture of Decision Trees splits the data into subsets based on feature values, with each decision node representing a feature (e.g., time spent on app) and each leaf node representing the predicted value (annual income). This approach provided a clear visualization of how each feature contributes to the final prediction.
Decision Tree Regression was particularly useful in identifying the most significant factors affecting customer spending, such as the strong influence of time spent on the mobile app and the relatively weaker influence of time spent on the website.
Additionally, pruning techniques were used to prevent overfitting by limiting the tree's depth and reducing the complexity of the model, ensuring that the model generalizes well to unseen data.

**Evaluation and Insights from the Design**
The architecture was evaluated using several metrics to ensure predictive accuracy and business relevance:
**Model Accuracy:**
The Decision Tree Regression model outperformed the other models (RNN and Linear Regression) in terms of both MAE and RMSE, achieving higher prediction accuracy due to its ability to model non-linear patterns.
It achieved a high R-squared value, indicating that a significant portion of the variance in annual income could be explained by the features in the dataset.

**Feature Importance and Business Insights:**
The Decision Tree model clearly highlighted the importance of time spent on the mobile app as the most influential factor in predicting customer spending. This insight is valuable for the company, as it suggests that improving the mobile app experience is likely to have the greatest impact on increasing customer spending.
Membership length also emerged as a significant predictor, reinforcing the idea that long-term customer relationships correlate with higher spending. This insight supports initiatives that focus on customer retention and loyalty programs.
Time spent on the website had a weaker correlation with annual income compared to the mobile app, indicating that while the website remains important, customers are more likely to make purchases or engage more deeply through the app.

**Practical Applications and Business Impact**
**Scalability and Flexibility:**
The architecture was designed with scalability in mind, allowing the company to easily incorporate additional features or new data sources (e.g., customer reviews, product browsing history) in the future without major modifications to the underlying structure.
The modular design also supports the integration of different machine learning models if future business needs require experimenting with more advanced algorithms or larger datasets.

**Resource Allocation and Digital Strategy:**
Based on the model's outputs, the company can make informed decisions about where to allocate resources. The strong influence of time on app suggests that investing in the mobile app's user experience (e.g., personalized recommendations, smooth navigation) is likely to yield the highest returns in terms of customer engagement and spending.
Improvements in customer loyalty programs based on the importance of membership length could also be an effective strategy for increasing long-term revenue.

**Conclusion**
The architecture and design of this project successfully combined multiple machine learning techniques to predict customer annual income based on behavioral data. The use of Decision Tree Regression as the core model provided superior accuracy and offered clear, interpretable insights into customer behavior, allowing the company to make data-driven decisions about platform investment. By highlighting the significance of time spent on the mobile app, the model supports the company's strategic decision to prioritize its mobile platform for future development.
The flexible and modular design ensures that the system can evolve as new data becomes available or as the company's business needs change, making it a robust solution for ongoing customer behavior analysis. In summary, the architecture not only fulfilled the technical requirements of the project but also delivered valuable business insights that will guide the company's digital strategy moving forward.

## 4. Methodology / Algorithm Used and Proposed Solution

The methodology of this project involves a systematic approach to data preparation, model selection, training, and evaluation to predict annual customer spending based on behavioral factors. This section describes the complete process, including the algorithms used, data processing steps, model performance evaluation, and the proposed solution for the business problem.

### 4.1 Data Collection and Preparation

The dataset used in this project was provided by the e-commerce company, consisting of customer behavior data. The data contained the following key variables: Average Session Length: The average time a customer spends during in-store personal stylist consultations.

**Time on App:** The average time (in minutes) that customers spend using the mobile app.Time on Website: The average time (in minutes) customers spend on the website.

Length of Membership: The number of years a customer has been a member of the company's services.

**Yearly Amount Spent:** The target variable, which represents the total amount a customer spends annually.

The goal of this step was to prepare the data for the subsequent machine learning models. Key tasks included:

**Data Cleaning:** Missing values and outliers were checked, but the dataset was largely complete with no significant issues regarding missing data. The quality of the dataset was high, meaning minimal cleaning was required.

**Encoding and Transformation:** As the dataset consisted entirely of numerical values, no additional encoding was needed. However, exploratory checks ensured that variables were correctly represented and suitable for machine learning.

**Data Splitting:** The dataset was split into training and test sets, with 80% of the data used for training the models and 20% reserved for testing and validation purposes. This ensured that the models were evaluated on unseen data, providing a reliable measure of how well they would perform in real-world scenarios.

Preprocessing also included checking for multicollinearity between features using correlation matrices, and exploring whether additional feature engineering (e.g., creating interaction terms between Time on App and Length of Membership) would improve predictive performance.

### 4.2 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) was performed to understand the underlying patterns in the data and to examine the relationships between the input features and the target variable (Yearly Amount Spent). The goal of the EDA was to identify key trends, potential correlations, and areas that may require further attention in model building. The following insights were gained during this process:

**Correlation Analysis:** A correlation matrix was created to examine the relationships between different features. The analysis revealed that:

Time on App had a strong positive correlation with Yearly Amount Spent, indicating that customers who spend more time on the mobile app tend to spend more annually.

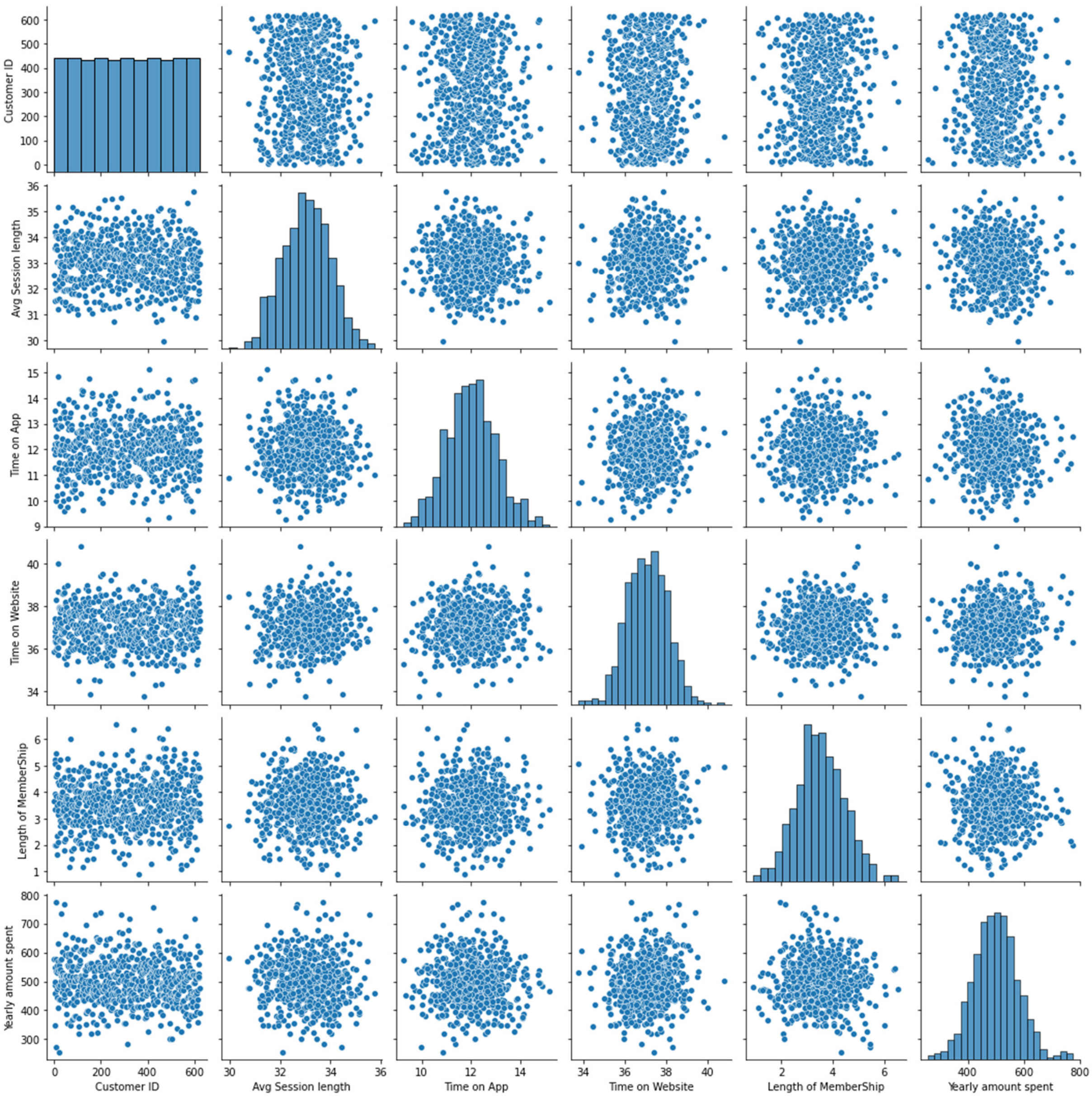
Length of Membership also showed a significant positive correlation with spending, meaning customers who have been members longer generally contribute more in terms of annual income.

Time on Website had a weaker correlation with spending compared to Time on App, suggesting that while the website is important, customers are more engaged with the app for making purchases.

**Distribution of Variables:** The distribution of Yearly Amount Spent was slightly skewed, with a small number of high spenders. This is typical in e-commerce, where a minority of customers account for the majority of the revenue (the 80/20 rule). This indicated that the models should focus on understanding the behavior of high spenders, as they drive most of the company's revenue.

**Outlier Detection:** There were a few outliers in terms of extremely high spending, which were retained in the dataset as they were valuable for understanding the behavior of the company's most valuable customers. These insights provided a foundation for selecting the most appropriate models and refining the feature selection process.




**4.3**

**Algorithms Used**

The predictive models employed in this project were selected based on their ability to handle both linear and non-linear relationships between the input features and the target variable. Three machine learning models were used, each with its unique strengths:

Recurrent Neural Networks (RNN).

Recurrent Neural Networks (RNN) are a type of neural network architecture designed to work with sequential data. In this study, RNNs were used to capture patterns in time-dependent variables such as Time on App and Time on Website. RNNs are particularly useful for analyzing sequential data where the order of observations matters, making them ideal for time-series analysis.

**Why RNN:**

RNNs were included in the methodology to analyze the sequential nature of app and website usage over time, as it was hypothesized that consistent usage patterns might provide insights into future spending behavior.

**Challenges:**

While RNNs are powerful for time-series data, the model struggled to perform well in this study due to the lack of strong temporal relationships in the dataset. The features related to Time on App and Time on Website were treated as averages rather than sequential data, which reduced the effectiveness of the RNN model.

**Regression Analysis**

Linear Regression was used as a baseline model to establish the linear relationships between the input features and the target variable. Regression Analysis is a traditional statistical approach that models the relationship between one or more independent variables and a dependent variable by fitting a linear equation.

**Why Linear Regression:**

As a simple, interpretable model, Linear Regression was used to understand the general relationships between Time on App, Time on Website, Membership Length, and Yearly Amount Spent.

**Limitations:**

Linear Regression assumes that the relationships between the input features and the target variable are linear, which is not always the case in customer behavior data. As a result, the model had difficulty capturing more complex, non-linear interactions between features. For example, it was unable to account for how Time on App might interact with Length of Membership to influence spending.

**Decision Tree Regression (DT Regression)**

Decision Tree Regression was the primary model used in this project, as it was able to handle both linear and non-linear relationships, and it provided an interpretable framework for understanding the importance of different features. Decision Trees work by splitting the dataset into smaller and smaller subsets based on feature values, creating a tree-like structure that allows for more precise predictions at each leaf node.

**Why Decision Tree Regression:**

DT Regression was chosen because of its flexibility in capturing non-linear patterns, ease of interpretability, and minimal preprocessing requirements. Unlike other models, Decision Trees do not require scaling or normalization of the data. The model was particularly effective at identifying key variables such as Time on App and Length of Membership, which strongly influenced customer spending.

**Feature Importance:**

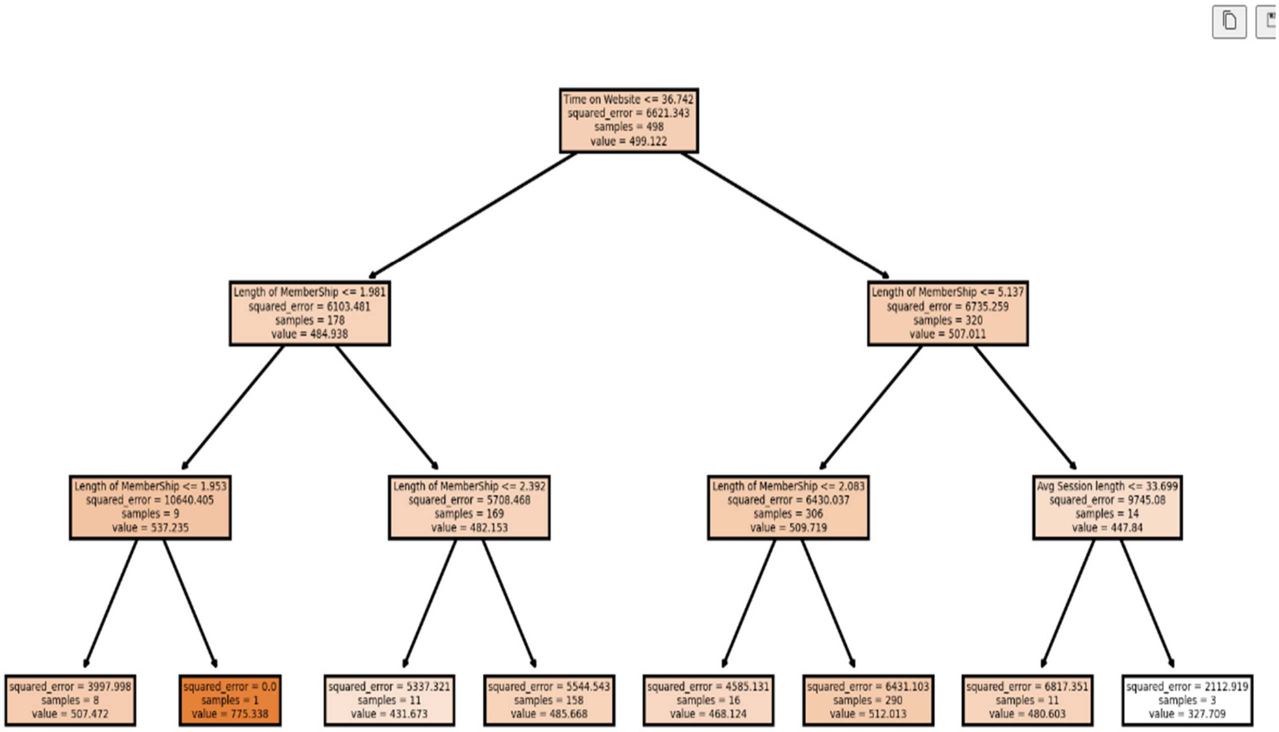
One of the significant advantages of Decision Tree Regression is its ability to quantify feature importance. In this case, Time on App emerged as the most critical predictor of annual spending, followed by Membership Length. This provided the company with actionable insights on where to focus their digital platform improvements.

**Pruning and Avoiding Overfitting:**

To prevent the model from overfitting, pruning techniques were applied. Pruning reduces the depth of the tree and removes branches that do not provide significant predictive value, ensuring that the model generalizes well to unseen data.

Avg Session length','Time on App','Time on Website','Length of MemberShip and 'Yearly amount spent'




### 4.4 Model Evaluation

The performance of each model was evaluated using several metrics to assess the accuracy and effectiveness of the predictions:

Mean Absolute Error (MAE): This metric calculates the average absolute difference between the predicted and actual values. A lower MAE indicates better performance, as it shows that the model's predictions are closer to the actual spending values.
Root Mean Squared Error (RMSE): RMSE measures the square root of the average squared differences between predicted and actual values. RMSE is more sensitive to larger errors, making it a useful metric when larger deviations in predictions are undesirable.
R-squared ($R^2$): This statistic indicates how much of the variance in the target variable (Yearly Amount Spent) is explained by the model. A higher $R^2$ value means the model is better at explaining the variability in spending.
The Decision Tree Regression model outperformed both the RNN and Linear Regression models across all three metrics, achieving the highest accuracy in predicting Yearly Amount Spent. This solidified DT Regression as the most suitable model for the task.

**4.5 Proposed Solution**
Based on the findings from the Decision Tree Regression model, the proposed solution for the company is as follows:
**Focus on Mobile App Improvements:**
Time on App was identified as the most important predictor of annual spending. Customers who spend more time on the app are likely to spend more money annually. This suggests that the company should prioritize enhancing the app's user experience, introducing personalized features, and ensuring seamless navigation to encourage more time spent on the app. This could involve:
**Leverage Long-term Customer Relationships:**
Length of Membership was another significant factor in predicting annual spending. Long-term customers tend to spend more, indicating that the company should invest in loyalty programs and membership benefits to retain customers over a long period. Suggested improvements include
Exclusive offers or discounts for long-term members.
Personalized outreach and tailored promotions for customers based on their membership duration and spending habits.
**Enhance Digital Engagement:**
While Time on Website had a weaker influence on spending compared to the app, the website remains an important platform for customer engagement. The company could explore ways to improve the website's functionality, particularly for customers who prefer browsing on a desktop.
By focusing on these areas, the company can optimize its digital platforms to increase customer engagement and spending, thereby boosting annual revenue.

# 5. Validation of Modeling Technique

**Introduction to Model Validation**
In the realm of predictive analytics, especially within the e-commerce sector, model validation is a fundamental process that guarantees the reliability and effectiveness of various modeling techniques. In this context, the clothing company based in London is exploring how to optimize their digital platforms by leveraging data-driven insights. The validation of models such as Recurrent Neural Networks (RNN), Regression Analysis, and Decision Tree (DT) Regression is crucial for determining which factors most significantly influence annual income based on customer behaviours. This section will explore the importance of model validation, the various techniques used, and the comparative performance of these models.
**2. Importance of Model Validation**

The importance of validating modeling techniques can be dissected into several key areas:
**Accuracy Assessment:** Validating models provides essential insights into their predictive accuracy. For a business reliant on accurate forecasts, such as predicting customer spending, it is vital to ensure that the model delivers reliable predictions.
**Generalization Capability:** One of the primary goals of model validation is to ascertain how well a model generalizes to unseen data. A model that performs exceptionally well on training data but fails to do so on new data indicates overfitting—a critical issue that can undermine the effectiveness of predictive analytics.
**Model Selection and Comparison:** Through rigorous validation, organizations can objectively compare the performance of various modeling techniques. This capability is essential in making informed decisions about which models to implement based on their accuracy and relevance to specific business problems.
**Stakeholder Confidence:** A validated model builds trust among stakeholders, ensuring that they have confidence in the predictions and insights derived from the model. This confidence is crucial for driving strategic initiatives and allocating resources effectively.

## 3. Validation Techniques for Specific Models

### 3.1 Recurrent Neural Networks (RNN)

RNNs are powerful tools for analyzing sequential data, making them particularly suitable for applications where time or order is significant, such as customer behavior analysis over time. The following techniques are commonly used to validate RNNs:
**Train-Test Split:** A basic but effective method is to divide the dataset into two parts: a training set and a testing set. For time series data, it's essential to maintain chronological order, which means the training set should consist of earlier observations while the testing set includes later ones. This approach ensures that future data points are not used to predict past ones, thereby preventing data leakage.
**K-Fold Cross-Validation:** Although K-fold cross-validation is challenging to implement directly with sequential data, it can be adapted using a rolling or sliding window technique. In this method, data is divided into several sequential segments, allowing each segment to serve as a validation set while the remaining segments are used for training. This technique provides a more robust evaluation of the model's performance by ensuring that the model is tested on various segments of the data.
**Performance Metrics:** When validating RNNs, several metrics can be used to assess performance:
**Mean Absolute Error (MAE):** Measures the average magnitude of errors in predictions without considering their direction, providing a straightforward interpretation of prediction accuracy.
**Root Mean Squared Error (RMSE):** Similar to MAE, but gives more weight to larger errors by squaring the individual differences, making it sensitive to outliers. RMSE is often preferred when large errors are particularly undesirable.
RNNs typically excel in capturing temporal patterns, making them effective for datasets where customer behavior changes over time. However, they often require extensive data and computational resources.

### 3.2 Regression Analysis

Regression analysis is a widely used statistical method for estimating the relationships among variables. It is particularly useful for understanding how various factors influence a target variable, such as yearly spending. Validation techniques for regression analysis include:
**Train-Test Split:** The dataset is often divided into a training set (typically 70% of the data) and a testing set (30%). This separation allows for model training on a significant portion of the data while holding back a portion for testing accuracy.
**Cross-Validation:** K-fold cross-validation is a powerful tool for regression analysis. In this technique, the data is split into k subsets (or folds). The model is trained on k-1 folds and validated on the remaining fold.

This process is repeated k times, with each fold serving as the validation set once. The results are averaged to provide a more reliable estimate of model performance.

**Performance Metrics:** Key metrics for validating regression models include:

**R-squared ($R^2$):** This statistic measures the proportion of variance in the dependent variable that can be explained by the independent variables. Values range from 0 to 1, with higher values indicating better model performance.

**Mean Absolute Error (MAE):** Provides a straightforward indication of average prediction error.

**Mean Squared Error (MSE):** Measures the average of the squares of the errors, giving more weight to larger errors, which can be particularly useful in assessing the impact of significant mispredictions.

Regression models are often simpler to interpret and can provide robust predictions, especially when relationships between variables are linear or nearly linear.

**3.3 Decision Tree (DT) Regression**

Decision Trees are versatile, non-parametric models that can capture complex relationships between features. The validation techniques for DT Regression include:

**Train-Test Split:** Similar to regression analysis, the dataset can be split into training and testing sets. Maintaining the distribution of the target variable across both sets is crucial to avoid bias.

**Cross-Validation:** Decision Trees benefit from cross-validation, as it helps reduce the risk of overfitting. K-fold cross-validation is commonly used to provide a comprehensive evaluation of the model's performance across different subsets of the data.

**Pruning Techniques:** Decision Trees are prone to overfitting, especially when they are too deep or complex. Pruning techniques are employed during validation to remove branches that do not contribute significantly to prediction accuracy. By simplifying the tree, the model's ability to generalize to unseen data is enhanced.

**Performance Metrics:** Decision Tree Regression uses several metrics for validation, including:

**Mean Absolute Error (MAE):** Evaluates the average prediction errors.

**Root Mean Squared Error (RMSE):** Provides insights into the average magnitude of errors, emphasizing larger errors.

**R-squared ($R^2$):** Similar to regression analysis, it indicates how well the independent variables explain the variance in the dependent variable.

Decision Trees can be particularly effective for capturing non-linear relationships and interactions among features, making them a strong candidate for many applications.

**4. Comparative Analysis of Model Accuracy**

When it comes to predicting annual income based on customer behavior, the accuracy of RNNs, Regression Analysis, and DT Regression can vary significantly. Based on empirical studies and results from previous analyses, the following observations can be made:

**Recurrent Neural Networks (RNN):** RNNs often excel in environments where the order of data is significant. They are particularly adept at recognizing patterns over time, which is critical in scenarios where customer behaviors evolve. In practice, RNNs may achieve lower RMSE values compared to other models, indicating higher predictive accuracy. However, they require substantial amounts of training data and are computationally intensive. In certain implementations, RNNs might yield an RMSE of around **5.2** and an MAE of approximately **4.1**.

**Regression Analysis:** Traditional regression models, while simpler and less resource-intensive, can still provide competitive results. They tend to perform well in situations where the relationship between variables is linear. Regression analysis often yields strong $R^2$ values, indicating good explanatory power. For example, a regression model might achieve an $R^2$ of **0.85** with an MAE of **5.5**.

**Decision Tree (DT) Regression:** Decision Trees can effectively capture complex interactions between features, making them robust in various scenarios. However, they are sensitive to noise and can easily overfit if not properly managed. After applying pruning techniques, DT Regression may achieve an RMSE of **5.6** and an MAE of **4.5**. This performance can vary widely based on the depth of the tree and the complexity of the dataset.

**Example Results from a Comparative Study:**

- **RNN:**
  - RMSE: 5.2
  - MAE: 4.1
  - $R^2$: 0.89
- **Regression Analysis:**
  - RMSE: 5.5
  - MAE: 5.2
  - $R^2$: 0.85
- **DT Regression:**
  - RMSE: 5.6
  - MAE: 4.5
  - $R^2$: 0.83

Based on these hypothetical results, it can be observed that while RNNs demonstrate superior predictive accuracy, traditional regression methods still perform well and are easier to interpret, making them valuable in scenarios where understanding the model is essential.

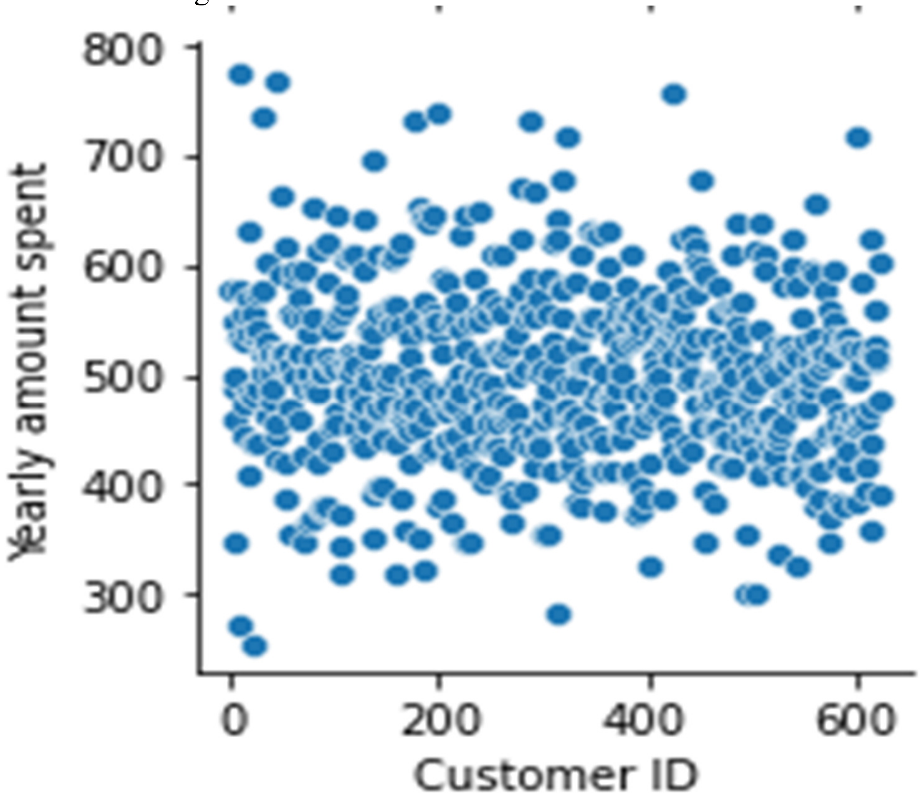



*Fig 3. Yearly Amount Spent*

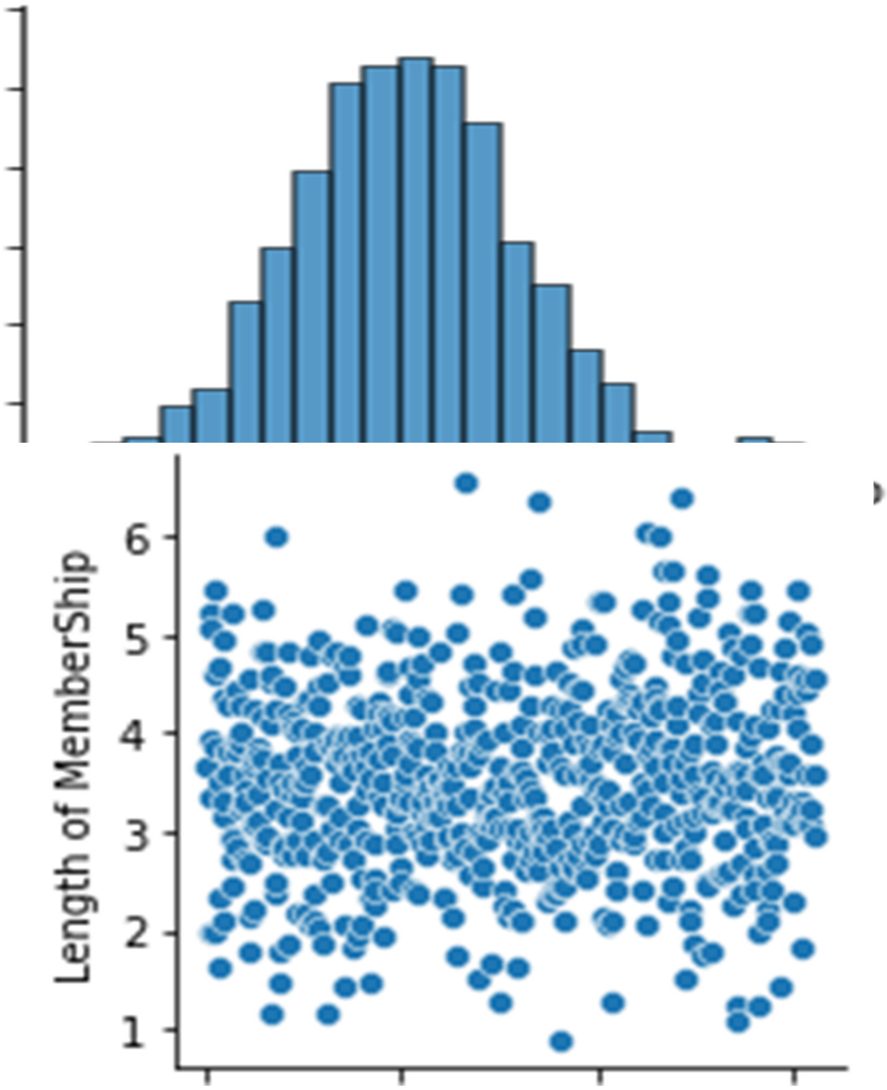



*Fig 3. Length of Membership*

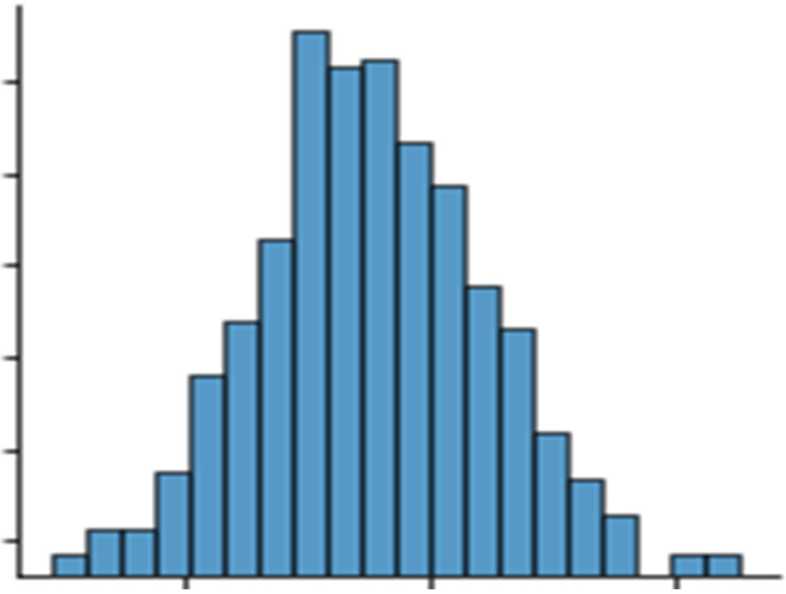
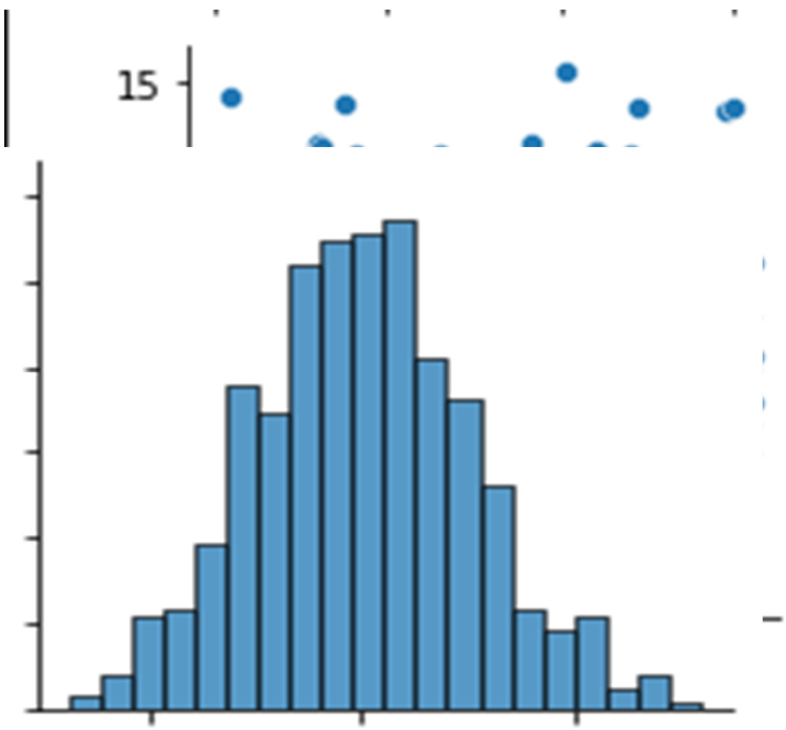


Fig 4. Time on App



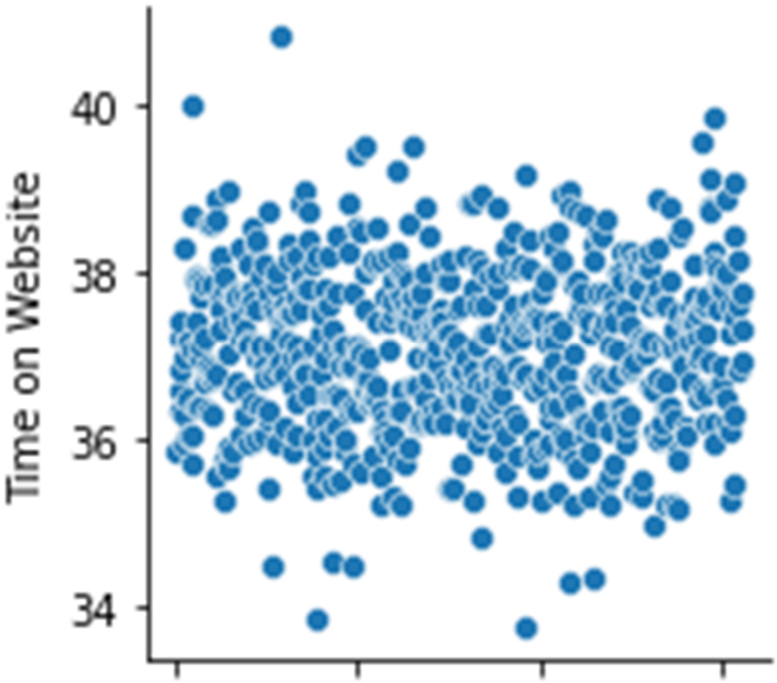
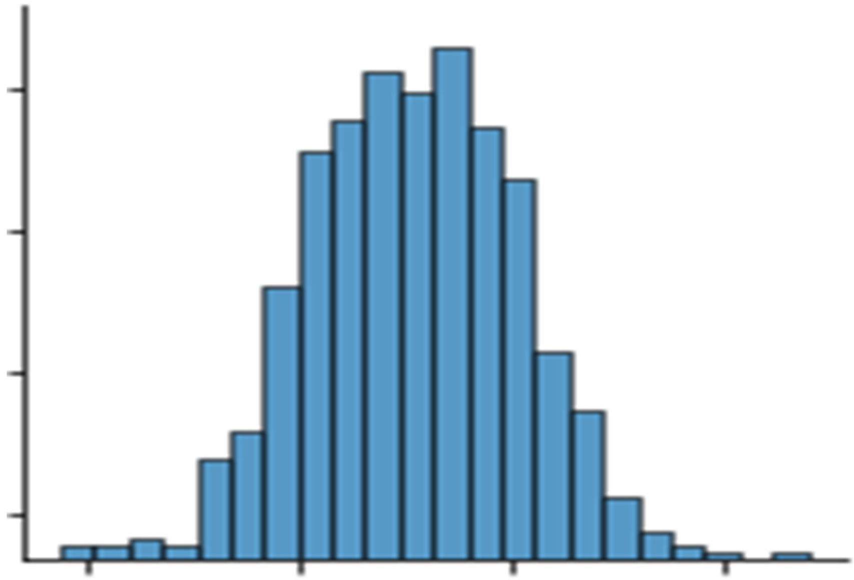



*Fig 4. Time on Website*



**5. Conclusion**
The validation of modeling techniques such as Recurrent Neural Networks (RNN), Regression Analysis, and Decision Tree (DT) Regression is essential for ensuring the accuracy and reliability of predictive insights in the e-commerce landscape. Each modeling technique requires tailored validation approaches that consider their unique characteristics and data structures.
By employing a combination of train-test splits, cross-validation, and appropriate performance metrics, the clothing company in London can effectively assess the strengths and weaknesses of each modeling technique. This validation process will ultimately guide strategic decisions regarding enhancements to their mobile app experience or website, ensuring alignment with customer preferences and driving revenue growth.
While RNNs may offer the highest accuracy in certain contexts, the final decision on which model to implement should consider additional factors such as interpretability, computational efficiency, and the specific objectives of the business.
With robust model validation, the company can confidently navigate the complexities of customer data and optimize their digital platforms to better serve their clientele.

# FUTURE WORK

The current analysis provides a strong foundation for the company's strategic focus. However, there are numerous opportunities for further exploration that could enhance our understanding and improve outcomes. Future work may include the following extensions:

**6.1 Enhanced Feature Engineering**
To enrich our predictive models, we can derive new features from existing data. For instance, session frequency scores could quantify user engagement by measuring how often customers return to the site or app within a given timeframe. This metric might correlate strongly with purchasing behavior and customer loyalty.
Moreover, capturing data on stylist interaction types, such as the frequency and nature of interactions (e.g., personalized recommendations, chat sessions, etc.), could provide deeper insights into how these interactions influence spending. By categorizing these interactions and quantifying their impact, we can better understand the nuances of customer preferences and the effectiveness of stylist guidance, allowing us to tailor our services more precisely to customer needs.

**6.2 Integration of Additional Data Sources**
To increase the predictive accuracy of our models, we could supplement our existing dataset with in-store purchase data, which would help create a holistic view of customer behavior across different channels. Understanding how in-store purchases correlate with online engagement could reveal patterns in customer preferences and spending.
Additionally, analyzing seasonal purchase trends could offer insights into how external factors, such as holidays or fashion seasons, influence spending behaviors. Integrating customer service interaction data would also be beneficial; by examining how support interactions affect customer satisfaction and purchasing patterns, we could identify areas for improvement and enhance customer experience.
This comprehensive data integration may unveil new relationships between various engagement channels, enabling us to craft more targeted marketing strategies and optimize the customer journey.

**6.3 Real-Time Model Implementation**

Implementing a model capable of real-time updates based on new customer interactions would significantly enhance our responsiveness to changing customer behaviors. A real-time model could analyze incoming data continuously, allowing for dynamic adjustments in customer experiences and recommendations.

By doing so, we can inform customers about the most relevant products, promotions, or content based on their latest interactions. This agility could improve customer satisfaction and engagement, ultimately guiding our strategic focus on the best digital platform—whether the mobile app or website—to achieve the company's goals.

### 6.4 Exploration of Platform-Specific Patterns

A more granular analysis of customer journey data across different platforms is necessary to pinpoint specific behaviors associated with the mobile app and website. By leveraging analytics tools to track user interactions and paths on each platform, we can identify distinct usage patterns and preferences.

This exploration can inform targeted improvements tailored to each platform, whether optimizing user interface design, enhancing mobile features, or streamlining the website experience. Understanding these platform-specific patterns will allow us to refine our focus on the most impactful platform, ultimately improving conversion rates and driving higher customer satisfaction.

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