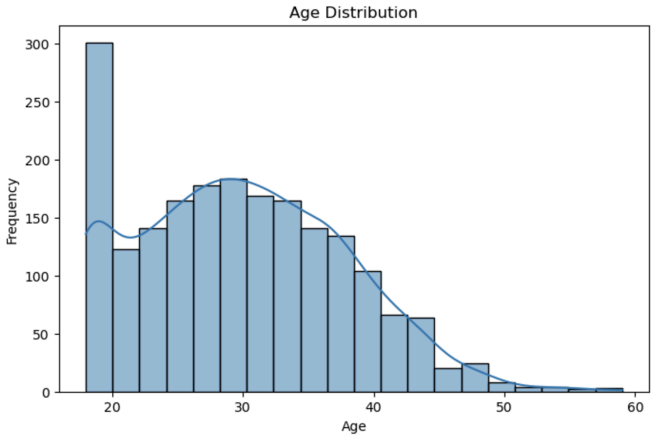
Databyday - Career Consulting Analysis

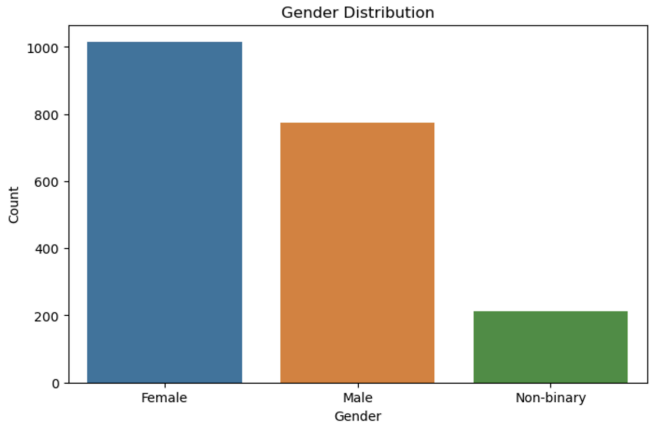
This analysis explores the simulated customer and sales data of *Databyday*, my career consulting business that aims to support individuals in learning the skills of a data analyst to pursue the profession. The primary goals are to:

1. Enhance **customer conversion** across product lines (1-on-1 career sessions, data eBooks, and affiliate marketing courses).
2. Improve **customer retention** and **product performance** through insight-driven strategies.

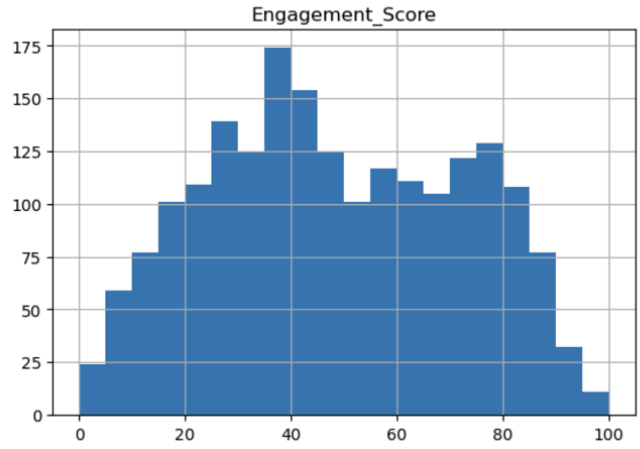
Demographic and Behavioral Insights

- **Demographics**:
    - Age: Customers primarily range from **20-40 years**.

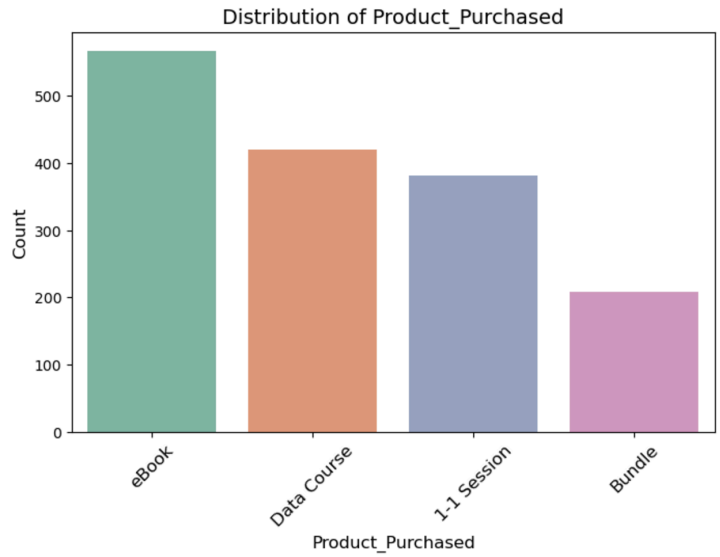




    - Gender: Slightly higher percentage of **female customers**.
    - Geography: Predominantly from **urban** and **suburban** areas.
- **Spending Behavior**:
    - Spend distribution is **bimodal**, with clusters of **low spenders (< $30)** and **high spenders (> $100)**.



    - Engagement scores have a **right-tailed distribution**, indicating a majority of users exhibit low engagement, with fewer highly engaged users.
- **Top Products**:

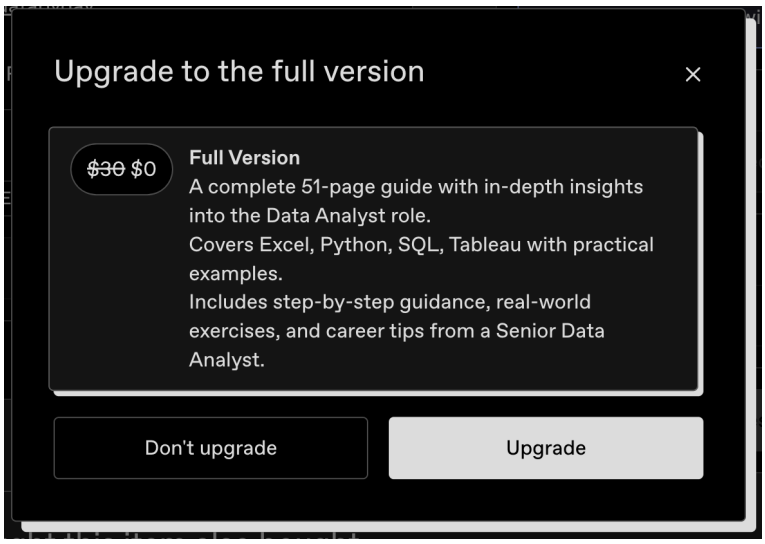


    - The **eBook** is the most purchased product.
    - The **data course** follows as the second most popular offering.

Upsell A/B Test Analysis

A/B test was conducted on users to determine the effectiveness of upsell messaging when adding the *How To Become A Data Analyst* eBook sample to their cart. The treatment group

receives the upsell message below while the control does not receive the message when selecting the trial version.



Key Results:

Group	Conversion Rate
Control	28.2%
Treatment	59.6%

- **P-value**: **< 0.0001**, indicating a statistically significant difference in conversion rates.

Recommendations:

1. **Deploy Upsell Messages**:
    - Roll out the upsell message to all users adding the eBook sample to their cart.
2. **Subgroup Analysis**:
    - Identify demographic or behavioral segments where upselling is most effective. We may also want to see if there is a subgroup, such as younger demographics in which the upsell message did not make any changes. For example, we may need other strategies outside of upsell messages to convince this demographic to make purchases.

Key Benefit: Improved conversions and revenue through targeted upsell strategies.

Funnel Analysis

Stage Breakdown:

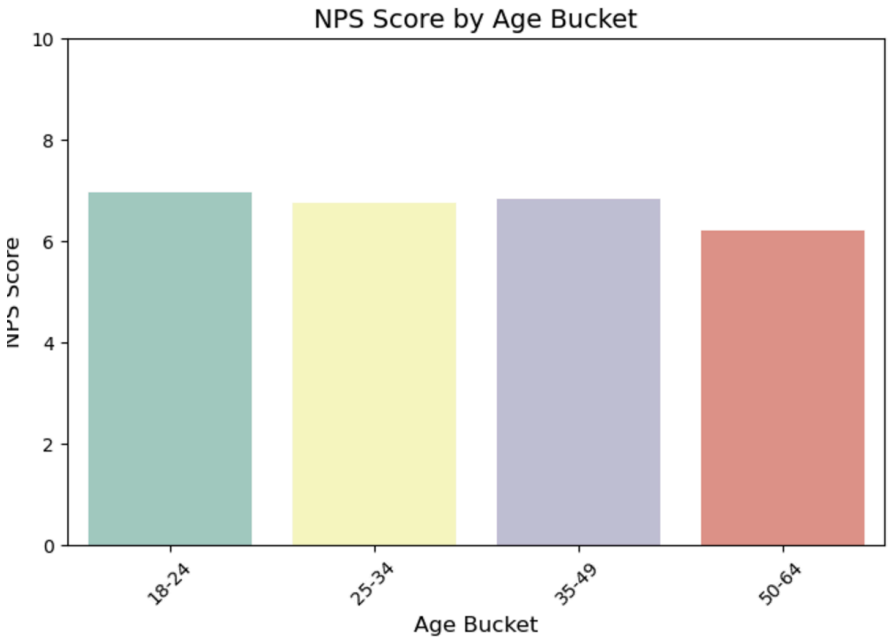
Stage	Count	Percentage	Conversion Rate
Lead	918	45.9%	-
Engaged	633	31.65%	68.95%
Converted	449	22.45%	70.93%

Insights:

1. **Strengths**:
    - High **Lead → Engaged** (68.95%) and **Engaged → Converted** (70.93%) conversion rates indicate effective top- and mid-funnel strategies.
2. **Opportunities**:
    - Investigate the **31% of leads** and **29% of engaged users** who do not convert:
        - Use segmentation to identify barriers (e.g., price sensitivity, unclear benefits of products).
        - Potentially test whether current price points deter leads from purchasing a product outside of the initial sample.

Product Performance

- **Average Spend Per User**: $48.14.
- **Distribution of Spend:** Most people spend $30 or less.



- **Net Promoter Score (NPS)**:
    - Scores across products are consistent (~7), with opportunities for improvement, especially for the 50-64 group. However, this group is not the target audience as databyday was initially aiming to support those from 18-30.

Recommendations:

1. Understand product purchases in the lower NPS individuals to improve the overall average NPS.
2. Enhance high-impact product features based on user feedback. Supplement the quantitative NPS measure with qualitative comments from customers could be helpful in understanding how databyday could improve products and services.

Predictive Modeling for Retention

After comparing multiple models, including a dummy classifier, Random Forest, and XGBoost, the recommendation is based on performance metrics, model complexity, and computational efficiency.

Model 0: Dummy Classifier (Baseline)

- **ROC AUC**: 0.50
- **Accuracy**: 0.59
- **Key Observations**:
    - The dummy classifier serves as a naive baseline.
    - It demonstrates how majority-class predictions would perform on the dataset.

Model 1: Random Forest (Initial)

- **ROC AUC**: 0.63
- **Accuracy**: 0.68
- **Key Observations**:
    - Random Forest showed an improvement over the dummy classifier, indicating that the model captures more relationships in the data.

Model 2: Random Forest (Additional Features)

- **ROC AUC**: 0.81
- **Accuracy**: 0.74
- **Key Observations**:
    - Random Forest with additional features showed a large improvement over the dummy classifier and the initial model, indicating that the model captures more relationships in the data.

Model 3: Random Forest (Recursive Feature Elimination)

- **ROC AUC**: 0.81
- **Accuracy**: 0.75
- **Key Observations**:
    - Recursive Feature Elimination (RFE) and hyperparameter tuning further refined the model, improving both recall and precision for the minority class (positive predictions).

Model 4: K-Fold Cross Validation

- **Best CV ROC AUC**: 0.8006
- **Test ROC AUC**: 0.815
- **Accuracy**: 0.75
- **Key Observations**:

- The cross-validated model confirmed the robustness of the results, indicating that the model performs well across different data splits.

Model 5: XGBoost

- **ROC AUC**: 0.81
- **Accuracy**: 0.74
- **Key Observations**:
  - XGBoost matched Random Forest's performance in terms of ROC AUC and accuracy.
  - As a boosting method, it is more computationally intensive but handles complex relationships in the data better, especially in cases where additional optimization may be required.

Recommendation: Random Forest (Recursive Feature Elimination)

Why Choose Random Forest?

1. **Similar Performance**:
   - Both Random Forest and XGBoost achieved comparable performance, with ROC AUC scores around **0.81** and accuracy at **0.74-0.75**.
   - The difference in performance is negligible.
2. **Computational Efficiency**:
   - Random Forest is faster to train and tune, especially with larger datasets or multiple hyperparameter candidates.
   - K-fold cross-validation with Random Forest required **1215 fits**, which was computationally expensive compared to Random Forest using recursive feature elimination.
3. **Ease of Use**:
   - Random Forest has fewer hyperparameters to tune and is easier to interpret, especially when using feature importance for explainability.

Next Steps

- Proceed with the **Random Forest model (Recursive Feature Elimination)**, as it balances performance and efficiency effectively.
- Utilize the selected features from RFE for streamlined predictions.
- If future datasets grow in complexity, consider revisiting XGBoost for potential gains in capturing non-linear relationships.

Action Plan

Immediate Steps:

1. **Upsell Messaging**:
    - Roll out proven upsell strategies across the user base.
2. **Funnel Optimization**:
    - Address key drop-off points such as when people select a sample ebook, but do not go on to purchase the full ebook.

Medium-Term Goals:

1. **Retention**:
    - Use predictive models to identify at-risk users and intervene early, such as with reminder marketing emails or discounts.
2. **Product Development**:
    - Leverage insights from NPS and perhaps gather qualitative feedback to understand how to enhance offerings.

Long-Term Goals:

1. **Scalable Marketing Strategies**:
    - Focus on high-performing segments and refine campaigns for maximum ROI.
2. **Continuous Improvement**:
    - Regularly update models and strategies to align with evolving business goals.