

Segmentation and Profiling Project

Introduction

For this project, I was tasked with developing a customer segmentation strategy as part of my role as Marketing Analytics Manager at VeroLink, a leading telecommunications company. With the data already cleaned and enriched with key fields, I set out to identify distinct customer segments that would drive informed economic decisions. The primary focus of the segmentation is customer tenure, complemented by an analysis of the number of devices, plans, services, and subscriptions customers are using. Additionally, the profiles incorporate demographic factors, with segments categorized based on tenure and risk. These segmentation profiles will enable VeroLink Communications to more effectively target specific customer groups, optimizing our outreach for both new and existing programs and incentives.

1 Summary of Findings

1.1 Setting the Stage

1.1.1 The Task at Hand

As a Marketing Analytics Manager, I regularly develop customer segments using demographic, behavioral, and transactional data. These segments are often leveraged by Verolink to guide the marketing team in creating effective strategies for engaging specific groups. For Verolink's latest marketing campaign, the focus is on understanding the customer profiles across various demographic factors. The marketing team is currently designing incentives targeting college students and young professionals, as well as developing rewards programs for loyal customers. My task is to analyze whether factors such as devices, plans, services, or subscriptions can be utilized to both retain at-risk customers and incentivize loyal customers.

1.1.2 Variables of Interest: What do we hope to learn about?

The variables of interest in this project were selected based on their ability to proficiently craft customer segments. Additionally, while there are many demographic fields available, I wanted to examine only the most useful for Verolink's latest marketing campaign. To determine the variables are of interest, I needed to consider:

- What variables will differentiate between high-risk and low-risk customers?
- Which variables will inform us about customer retention and engagement?
- Which demographic fields will allow us to create more personalized and targeted marketing campaigns?
- What are the key demographics of customers who are most likely to respond to our incentive and reward programs?

To address customer risk and retention, I considered factors such as customer tenure (in months or years), the number of plans, subscriptions, devices, and services each customer holds, as well as their usage hours for services and plans. Throughout the analysis, I used the variable "Provider Tenure (in months)" as the target variable to ensure that customer retention was prioritized. The segmentation variables I used were number of plans, monthly data usage, streaming hours, and voice service usage (see [Figures 11-19](#) in [Appendix](#)).

Once I determined the customer groups based on these variables and explored the impact various demographic variables had on each group, I concluded that the most important demographics to consider to optimize the success of the marketing campaign are:

- Age
- Region
- Employment Length
- Job Category
- Education Level

Other demographic variables, including gender and annual average income, were considered but had little to no impact on customer retention (see [Figures 24-31](#) in [Appendix](#)).

1.1.3 Customer Groups: Who do we want to learn about?

With my target variable of Verolink provider tenure (in months) and segmentation variables (number of plans, monthly data usage, streaming hours, and voice service usage), I used the supervised CART tree segmentation technique to create customer groups. The customer groups are shown in the table below with key statistical information regarding customer tenure.

Customer Group	Verolink Tenure (in months)					
	Mean	SD	Median	IQR	Minimum	Maximum
Newcomer	10.5	9.0	8	10	1	53
Emerging High Risk	21.4	11.5	20	18	0	55
Emerging Low Risk	28.3	15.0	27	23	0	69

Customer Group	VeroLink Tenure (in months)					
	Mean	SD	Median	IQR	Minimum	Maximum
Established High Risk	34.1	12.4	35	15.75	1	66
Established Low Risk	44.8	14.8	46	22	2	71
Veteran Low Risk	53.0	13.0	56	18	2	72
Long Term Low Risk	62.2	9.5	64	11	7	72
Loyal Low Risk	68.5	6.4	71	4	10	72

From this table, we can observe that both the mean and median tenure increase as we move down the groups. The variability is lowest in the extreme groups ('Newcomers,' 'Long Term Low Risk,' and 'Loyal Low Risk'), while the greatest variability is seen in the other 'Low Risk' groups.

1.2 Results

1.2.1 Tenure and Customer Engagement

Customer tenure was examined for each group via line graphs. As shown in [Figure 1](#), the most extreme lengths of customer tenure were found in the "Newcomer" and "Loyal Low Risk" groups, which also had the lowest variability of all the groups. The majority of customers in the "Newcomer" groups have been VeroLink customers for less than two years while the majority of customers in the "Loyal Low Risk" group have been customers for over 5 years.

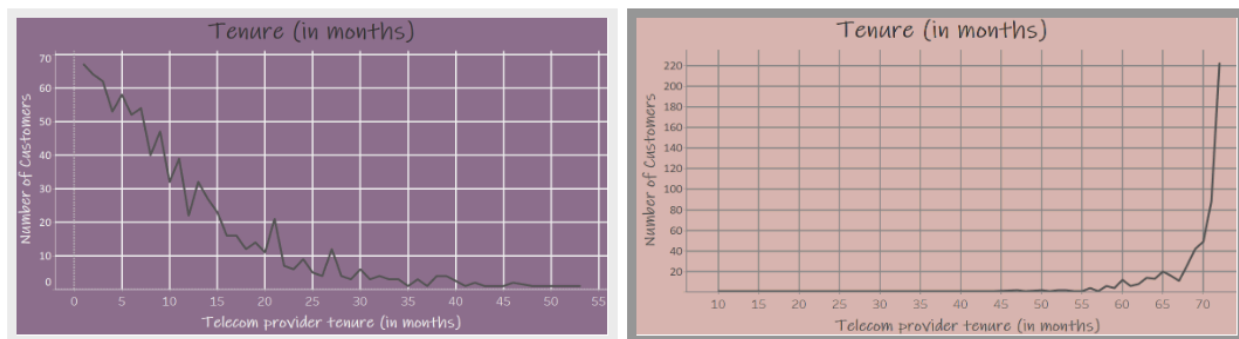


Figure 1 shows a side by side comparison of the most extreme customer groups - "Newcomers" (left) and "Loyal Low Risk" (right).

The line graphs representing the other groups indicated more variability in between the lengths of time in customers' tenure at VeroLink, particularly "Emerging High Risk", "Emerging Low Risk", "Established High Risk", and "Established Low Risk". The distribution of these graphs is roughly symmetrical. Contrastingly, "Veteran Low Risk" and "Long Term Low Risk" show less variability with a left skewed distribution - as anticipated given their longer average tenure at VeroLink.

To examine customer engagement, I looked at the number of devices, plans, services, and subscriptions across regions of the country. In addition to demonstrating how much customers have invested into the company through their engagement, this also provides insight into where in the United States the initiative and reward programs may be most effective. For example, as seen in [Figure 2](#), the "Long Term Low Risk" has varying distributions across regions. There are more customers with 0-1 devices in the Northeast and Southeast than in other regions. However, all customers in the Northeast and West Coast regions have at least one plan they are enrolled in. Therefore, an incentive or reward encouraging customers to purchase devices will be more beneficial in the Northeast region. Across all regions, most customers in this segment participate in zero services and have 1-3 subscriptions.

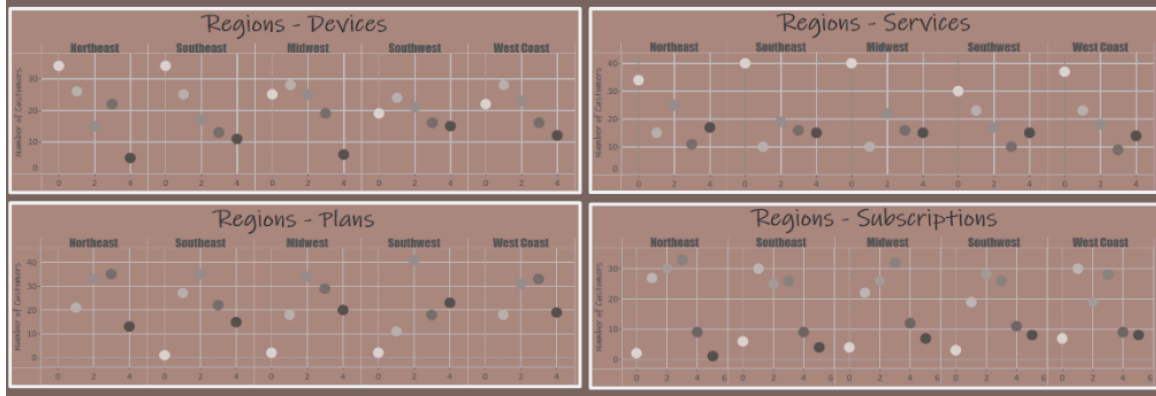


Figure 2 shows a breakdown of the number of devices, plans, services and subscriptions across regions of the country for the “Long Term Low Risk” customer group.

Surprisingly, the “Newcomer” and “Loyal Low Risk” customer segments have comparable breakdowns across regions, with a small shift in the data towards the right for the more tenured group. For example, most of the customers in the “Newcomer” group have 0-2 subscriptions while most of the customers in the “Loyal Low Risk” group have 1-3 subscriptions.

Another noteworthy result is that in the “Emerging High Risk” and “Established High Risk” groups, zero customers are enrolled in plans across all regions, indicating that using an incentive for plan enrollment could be a tactic to “hook” these customers into staying.

1.2.2 Age Groups

As the tenure of the groups increases, so does the typical age bracket. The bar graphs for “Newcomer”, “Emerging High Risk”, and “Emerging Low Risk” are right skewed, indicating that the average age is lower in these age brackets. The distribution of ages in the “Established High Risk” group is roughly uniformly distributed while the distribution of ages in the “Established Low Risk” group is symmetrical, with the majority of customers being middle aged. “Veteran Low Risk”, “Long Term Low Risk”, and “Loyal Low Risk” are increasingly left skewed and thus have increasingly older customers.

1.2.3 Employment and Education Level

The length of employment aligns as expected with the ages of each of the customer groups, with the younger groups having less years of employment overall and the older groups having more years of employment overall. [Figure 3](#) shows a visual representation of this relationship; in the “Emerging Low Risk” group, most customers have been employed for less than 5 years while the distribution of customers is more spread out across years of employment for the “Long Term Low Risk” group.

Upon examining the graphs of all customer segments, most customers have a Post-Secondary Education level, with those points well above the rest on all graphs. Also, most of the customers with no high school education are employed for fewer years across all graphs.

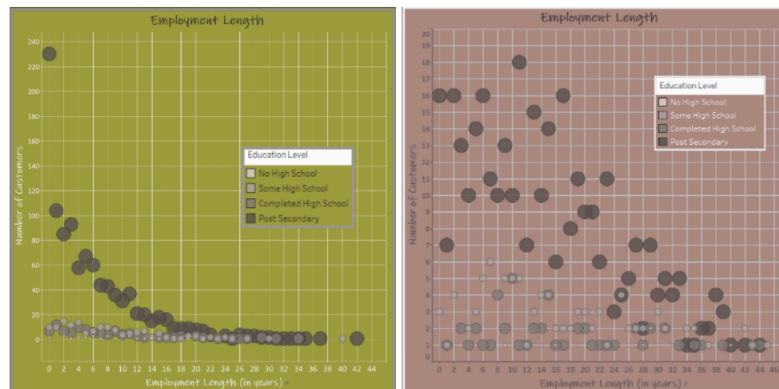


Figure 3 shows the number of customers with different lengths of employment in years broken down by education level for the “Emerging Low Risk” group (left) and the “Long Term Low Risk” group (right).

1.2.4 Job Category

Customers in the “Newcomer”, “Emerging High Risk”, “Emerging Low Risk”, and “Established High Risk” segments have jobs primarily in sales and then professional fields. In the “Established Low Risk”, “Veteran Low Risk”, and “Long Term Low Risk”, the number of customers in the sales and professional fields is almost identical. While “Loyal Low Risk” also has a significant number of customers in a professional field, it is the only group in which “Labor” is one of the top two job categories. Across all eight segments, the agriculture job category has the least number of customers the crafts job category has the second least number of customers.

1.3 Next Steps

1.3.1 Recommendations

High risk groups should be considered for incentive programs in order to increase customer engagement and, therefore, the likelihood of retaining these customers. With zero customers enrolled in plans in both the “Emerging High Risk” and “Established High Risk” customer segments, introducing an incentive program for plans. I recommend that VeroLink considers the plans that will appeal to a younger demographic (18 to 34 years old) who are employed in the sales job category. Alternatively, a high number of customers also own zero devices in both of these segments; providing customers with a free device may incentivize them to purchase plans that utilize their free devices.

Committed customers in the “Veteran Low Risk”, “Long Term Low Risk”, and “Loyal Low Risk” segments could be considered for loyalty rewards programs. Across all three groups, most customers are enrolled in at least one plan and at least one subscription. However, the frequency does vary from group to group as well as between regions. Thus, VeroLink may consider offering different loyalty programs in different regions. These rewards programs should be geared toward an older demographic (45 to 75 years old) based on the age breakdown of these customer segments.

1.3.2 Future Work

Moving forward, to better develop incentive and reward programs based on customer needs or preferences, I recommend breaking down the devices, plans, services, and subscriptions by type for the customer segments of interest. This will help inform us about what to use as incentives and rewards. Furthermore, this could help VeroLink gear these programs to the demographics of the desired customer segments.

Additionally, I strongly recommend gathering data based on customer churn to determine characteristics of customers that are leaving VeroLink.

2 Technical Details

2.1 Segmentation Technique

2.1.1 Variables of Interest

Upon careful consideration of the available variables, I chose to use the Provider Tenure (in months) as my target variable. When examining the distribution of this variable in R, I discovered that the data was roughly symmetric and uniform with the exception of the 70-75 months bin, which had over 600 customers (see [Figure 11](#) in the [Appendix](#)). I then identified the variables listed below as potential foundations for my segmentation techniques, as they reflect customer engagement.

- Number of Plans
- Number of Subscriptions
- Number of Devices
- Number of Services
- Equipment Monthly Usage
- Monthly Data Usage
- Voice Service Usage
- Streaming Hours

To help inform my decision, I created graphical representations of these variables (see [Figures 12-19](#) in the [Appendix](#)). Because these graphs reveal a significant number of customers with zero hours of equipment usage and no monthly data usage, I chose to create binary fields for Equipment Monthly Usage and Monthly Data Usage. If the value of the variables was zero, I assigned the value “No” to the new variable, otherwise I assigned the value “Yes”. I named the new variables created Equipment Use and Data Use.

2.1.2 Supervised: CART Segmentation

Since I was not using exclusively non-binary variables, I decided that the supervised CART tree segmentation technique in R would be an appropriate choice. With my target variable of provider tenure, I started by looking at a CART tree broken down by number of plans and data use (see [Figure 20](#) in the [Appendix](#)). This resulted in 5 segment groups that were not all distinctly different. I then decided to experiment using other combinations of variables as the basis of my CART tree (see [Figure 21](#) and [Figure 22](#) in the [Appendix](#)). After using the results of my segmentation results to create a “Voice Service Groups” variable and “Streaming Groups” variable, I finally found a combination that produced satisfactory results. The winning combination was number of plans, data use, streaming groups, and voice service groups and resulted in eight distinct customer segments shown in [Figure 4](#).

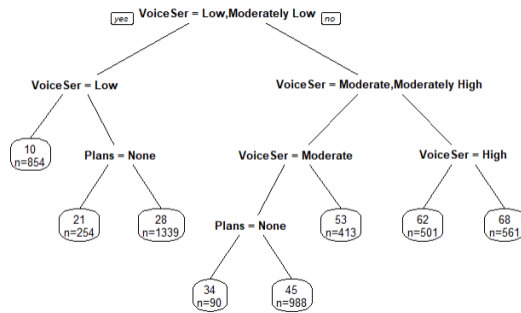


Figure 4 shows the CART tree created using provider tenure (in months) as the target variable and number of plans, data use, streaming groups, and voice service groups as segmentation variables.

2.1.3 Unsupervised: K-means Segmentation

Wanting to see the results of using exclusively quantitative variables, I chose to also run a K-means segmentation in R based on the number of plans, monthly data usage, streaming hours, voice service usage, and provider tenure (in months). This produced [Figure 5](#); based on the visualization I determined that 6 or 7 segments would be most appropriate and chose to proceed with 6 segments.

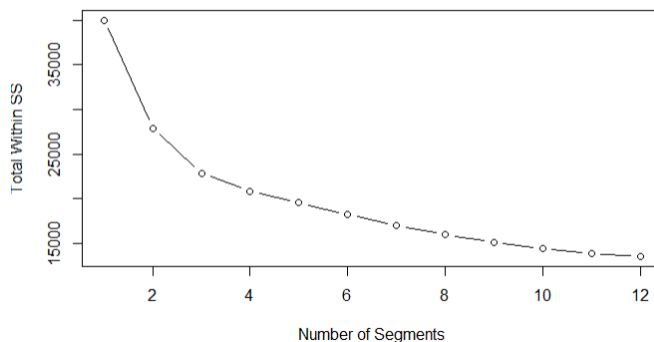


Figure 5 shows the plot of the total within-cluster sum of squares (tot_within_ss) for each number of clusters.

2.1.4 Selecting a Segmentation Solution

Having created two different sets of customer segments, I turned to Tableau to create visualizations to compare the two distinct groupings. I examined visualizations based on demographic variables including age, gender, education level, annual household income, region, and employment length.

[Figure 6](#) shows a side by side view of the visualizations created to represent age from each of the segmentation techniques. The CART segments show a clear pattern, with customer tenure increasing as age increases. The graph shows that the values of the segments are aligned with the average tenure of each group, with segment 1 having the lowest average tenure and segment 8 having the highest average tenure. An interesting observation is that segments 6, 7, and 8 have a significantly lower tenure for the 18-24 year old age group when compared to the other values in the respective segments. The most notable outlier is highlighted by the tool tip, showing that 23 customers are in the 18-24 year old age group for segment 7 with an average provider tenure of 23 months. The K-means segment visualization shows that age does not seem

to have a huge impact on tenure, particularly for segments 1, 3, and 4 - which are almost identical. Furthermore, there are no customers in the 18-24 year old age group in segment 5.

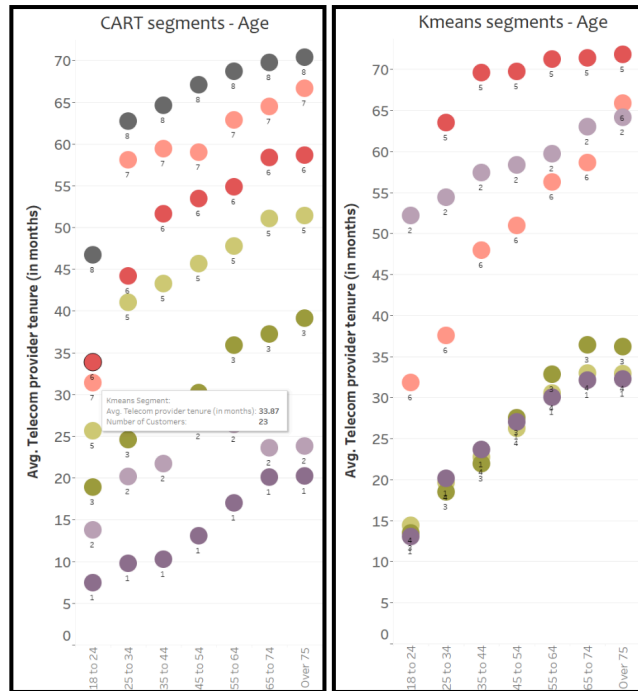


Figure 6 shows a side-by-side comparison of the age versus average provider tenure (in months) for the CART segments (left) and K-means segments (right).

I next looked at the breakdown of gender across customer segments for both segmentation techniques. Based on my analysis, I concluded that gender had little impact on customer tenure for either of the segmentation techniques. The graphical representations used for this analysis can be seen in (see [Figures 24-31](#) in [Appendix](#)).

When examining education level and income, the CART segments once again revealed more variation between customer segments (see [Figures 26-28](#) in [Appendix](#)). While other customer segments varied based on both average annual household income and average provider tenure, segments 1, 3, and 4 had almost identical annual household incomes of about \$40,000 (see [Figure 26](#) in [Appendix](#)). When looking at the same information broken down by education level, a similar pattern emerged for all levels of education. The bar chart illustrating average provider tenure across different education levels shows a similar distribution for each segment within those levels (see [Figure 27](#) in [Appendix](#)). The K-means visualizations also showed little to no difference between segments and the same variables (see [Figures 29-31](#) in [Appendix](#)).

Plots created to determine the number of customers in each region across customer segments were also created to compare the two segmentation techniques (see [Figures 32](#) and [33](#) in [Appendix](#)). The CART segments showed little variation in the number of customers per region with the exception of segment 7, which had slightly more customers than segment 8 in the southeast; elsewhere, as the order of the segments remained constant across the regions. Similarly, the ranking of number of customers across regions was consistent for the K-means segments; however, there was more variation between the regions within each segment. The size of the points and labels in both plots indicates the average provider tenure in months, showing very little variation between regions for both groupings.

Finally, scatter plots were created to compare employment length in years and average provider tenure (see [Figures 34](#) and [35](#) in [Appendix](#)). The CART customer groupings showed significant variation between segments 1, 2, 3, 4, and 5. Segments 6 and 7 also had some variation while segment 8 remained fairly consistent over different lengths of employment. For all segments, the average provider tenure was noticeably lower when employment length was zero years. The K-means segments showed less variability, with segment 5 having almost a constant average provider income across all employment lengths. All other segments had increasing average provider tenure as the employment length increased. Segments 1, 3, and 4 followed a similar pattern when employment length was less than 10 years but diverged after that.

Based on my observations from the visualization, I concluded that the CART segmentation resulted in more unique groups based on my variables of interest. Therefore, I chose to use the eight customer segments created by the CART tree segmentation based on number of plans, data use, streaming groups, and voice service groups. The eight customer segments were used to create the profiles in section 2.2.

2.2 Customer Profiles

The segments used to create the customer profiles described below were named based on the length of customer provider tenure (observed through the mean and visualizations) as well as customer engagement (observed through visualizations breaking down the number of devices, plans, services, and subscriptions). The customer profiles can be viewed in their entirety in [Figures 36 - 43](#) in the [Appendix](#).

2.2.1 Segment 1: “Newcomer” (see [Figure 36](#) in the [Appendix](#))

Customers in the “Newcomer” segment have an average tenure at Verolink of 10.5 months (less than 1 year). Based on the line plot, most customers in this segment have been at Verolink for less than 18 months (1.5 years). These customers show some engagement with most of them having 1-3 devices, 0-2 plans, and 0-2 subscriptions. It is worth noting that most of the customers from the midwest have 3 devices and most of the customers from the northeast have 1 plan. Across all regions, most customers are not enrolled in any services. The distribution of ages in this segment is right skewed, with the majority of customers between 18 and 44 years old. The majority of this group have a job in sales and a post secondary education level. The majority of customers have completed high school and have been employed for less than 10 years.

2.2.2 Segment 2: “Emerging High Risk” (see [Figure 37](#) in the [Appendix](#))

The second segment is composed of customers who have been at Verolink for a relatively short time and are less engaged with the devices, plans, services and subscriptions, as shown in [Figure 7](#). The “Emerging High Risk” segment has an average tenure at 21.4 months, with most customers having a tenure between 6 months and 36 months (3 years) based on the line plot. Across all regions, most customers do not have any devices, plans, services, or subscriptions. The distribution of ages is slightly less skewed, but still on the younger side with most of the customers between 18 and 54 years old. Most of the customers in this segment are employed in the sales or professional job categories. The education level of customers in this segment is more varied, but still mostly at the post secondary level. The right side of the Employment Length graph shows that there are 5 customers with less than a high school level education who have been employed for over 25 years.

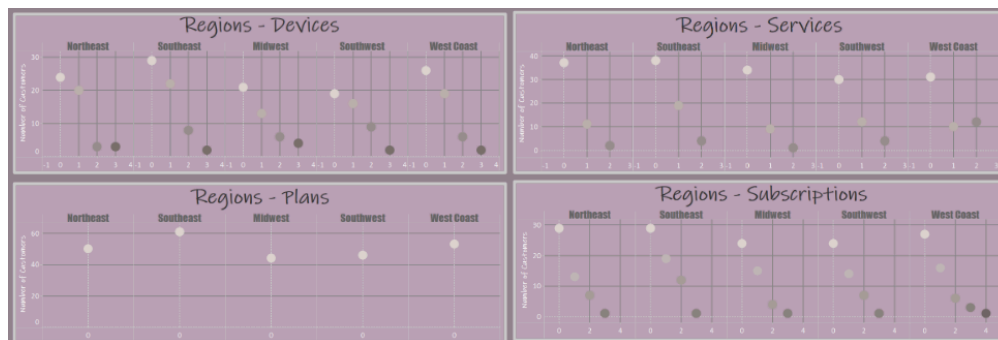


Figure 7 shows a breakdown of the number of devices, plans, services and subscriptions across regions of the country for the “Emerging High Risk” customer group.

2.2.3 Segment 3: “Emerging Low Risk” (see [Figure 38](#) in the [Appendix](#))

The “Emerging Low Risk” customer segment has a wider range of provider tenure, with the line plot showing that the majority of customers range from 6 months to 48 months (4 years). The average tenure for this group is 28.3 months. The distribution of devices and subscriptions is almost identical across regions, with most customers having 3 devices and 2 subscriptions, indicating that this group is more engaged and less of a risk. While all regions show that most customers do not have any plans, more customers from the west coast have 3 plans than any other region. A larger majority of customers in the southeast region do not have any services than in other regions. The ages are once again less skewed than the previous segment with the majority of customers falling between 25 and 54 years of age. Similar to the “Emerging High Risk” segment, customers in this segment work primarily in sales and professional job categories. The majority of customers in this segment have a post secondary education level and an employment length of less than 15 years.

2.2.4 Segment 4: “Established High Risk” (see [Figure 39](#) in the [Appendix](#))

Customers in the “Established High Risk” segment have a longer, less varying tenure shown in [Figure 8](#). The majority of customers have a tenure between 24 months (2 years) and 54 months (4.5 years); the average length of tenure is 34.1 months. None of the customers in this group have plans and most of the customers have no devices and no services. The majority of customers in the northeast, southwest, and west coast regions have no subscriptions and the majority of customers in the southeast and midwest have 1 subscription. These findings indicate low engagement and high risk within this segment. The ages of “Established High Risk” customers are relatively uniform, with the exceptions of significantly more customers in the 25 to 34 age group and significantly less customers in the over 75 age group. Like the last two segments described, the majority of customers in this segment have jobs in the sales or professional categories. Most customers in this segment have employment lengths less than 10 years. There are a closer number of customers with post secondary, completed high school, and some high school than previous segments; however, there are still fewer customers with no high school education.

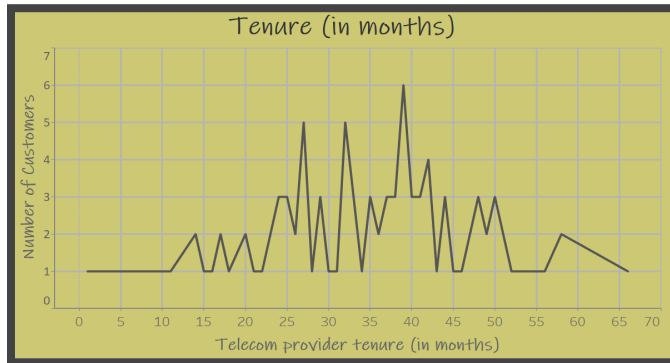


Figure 8 shows the distribution of provider tenure for the “Established High Risk” segment.

2.2.5 Segment 5: “Established Low Risk” (see [Figure 40](#) in the [Appendix](#))

Segment 5 contains “Established Low Risk” customers. The line plot shows that the distribution of tenure is skewed to the left; most customers have a tenure of 24 months (2 years) to 65 months (5.5 years) and the mean tenure is 44.8 months. Customers in this segment are highly engaged and thus a low risk as they all have at least 1 plan; the west coast region shows that a roughly equal number of customers has 1, 2, 3, and 4 plans. Most of the customers in the midwest and southwest do not have any devices but most of the customers in the northeast, southeast, and west coast have three devices. The majority of customers across all regions do not have any services and have 1 to 3 subscriptions. The distribution of ages is shown in [Figure 9](#); this bar graph shows a roughly symmetric distribution with the highest bar showing that almost 200 customers in this segment are in the 45-55 year old age group. An essentially equal number of customers have jobs in the professional and sales category, representing more than half of the customers in this segment. The employment length graph shows that most “Established Low Risk” customers have less than 20 years of employment and a post secondary education level.

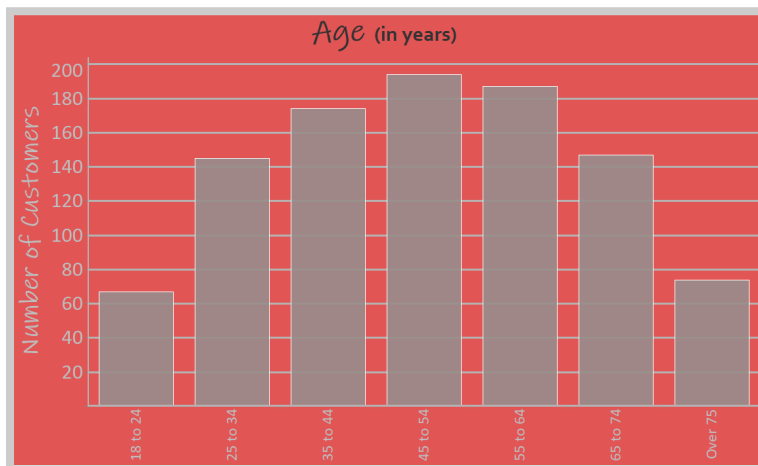


Figure 9 shows the distribution of ages for the “Established Low Risk” segment.

2.2.6 Segment 6: “Veteran Low Risk” (see [Figure 41](#) in the [Appendix](#))

The next segment represents “Veteran Low Risk” customers, who have been customers for an average of 53 months. The distribution of provider tenure is even more drastically skewed left than the “Established Low Risk” segment, with most customers having a tenure of 24 months (2 years) to 72 months (6 years). The number of subscriptions also has a similar distribution with most customers having 1-3 subscriptions. Across all regions, most customers have 0-2 services and devices. Notably, the southwest has an almost equal number of customers with 0, 1, 2, and 3 devices. The ages of these customers are also more skewed left with the typical age between 45 and 74 years old. Customers usually have 1 or 2 plans across all regions. The breakdown of job categories once again shows that the top categories are sales and professional. There are more customers in this category with at least 2 years of employment; two of the customers with no high school education have been working for over 40 years. Overall, the breakdown of employment length and education level is more varied in this segment than others, as seen in [Figure 10](#).

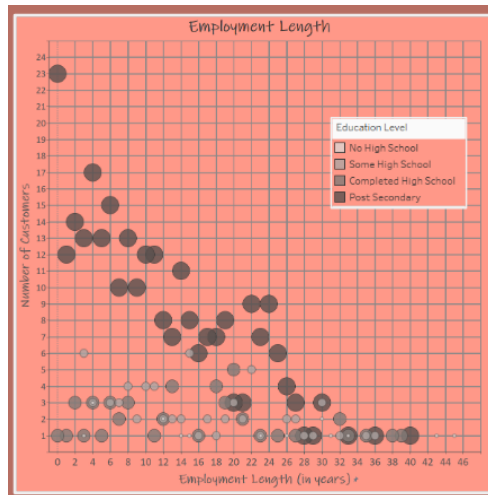


Figure 10 shows the number of customers with different lengths of employment in years broken down by education level for the “Veteran Low Risk” group.

2.2.7 Segment 7: “Long Term Low Risk” (see [Figure 42](#) in the [Appendix](#))

The “Long Term Low Risk” group has few customers with a tenure of less than 48 months (4 years). The line plot has highly skewed left, with most customers between 54 months (4.5 years) and 72 months (6 years) and an average tenure of 62.1 months. Engagement in this group is varied, but still indicates lower risk, especially considering the length of tenure. All customers from the northeast and west coast have at least one plan and most customers in all regions have between 1 and 3 subscriptions. Also across all regions, most customers have 0-1 devices and 0-2 services. Age is skewed to the left with the majority of customers between 55 years old and 74 years old. About half of the customers who are “Long Term Low Risk” have jobs in the professional or sales categories. The number of customers decreases as the length of employment increases, similar to the other segments studied. However, the distribution of customers is more varied across employment lengths and education levels.

2.2.8 Segment 8: “Loyal Low Risk” (see [Figure 43](#) in the [Appendix](#))

The final segment is customers who have an average tenure of 68.5 months; the line plot showing provider tenure is highly skewed left with almost all customers having a tenure of 60 months (5 years). Across all regions, all of the customers in this segment have at least one plan. Customers from the northeast and midwest have at least one subscription with few customers from the other regions having no subscriptions. In comparison, more customers across all regions have no devices or no services. However, there are still a significant number of customers who have between one and three devices. The ages in this segment are also significantly skewed to the left with the majority of customers over 55 years old. In contrast with other segments, customers in the “Loyal Low Risk” segment are most likely working in a job that falls in the professional or labor category (not sales). This customer segment has a greater variation of education levels. The distribution of employment length also differs from other segments, with the majority of customers having at least 9 years of employment.

3 Appendix

3.1 Variables of Interest

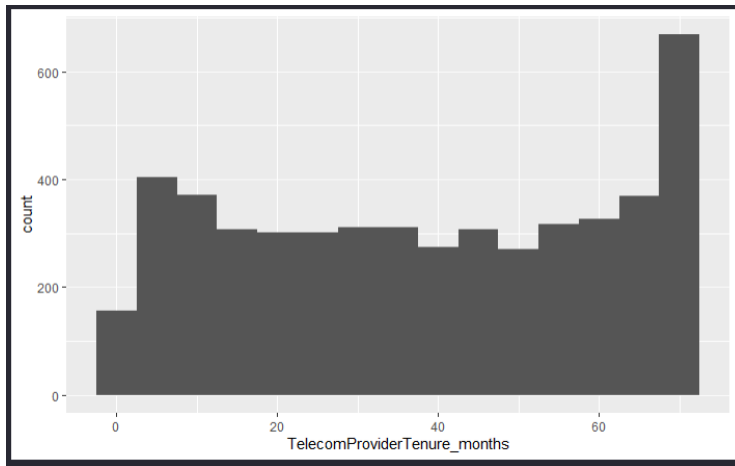


Figure 11 shows the distribution of customers across provider tenure, created in R.

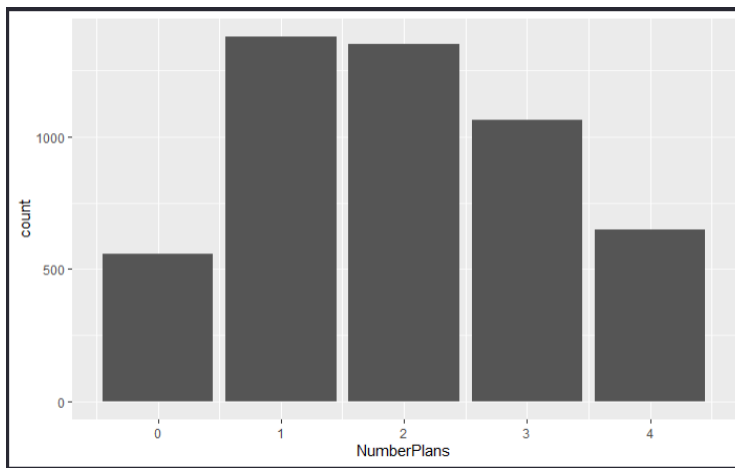


Figure 12 shows the distribution of customers across the number of plans, created in R.

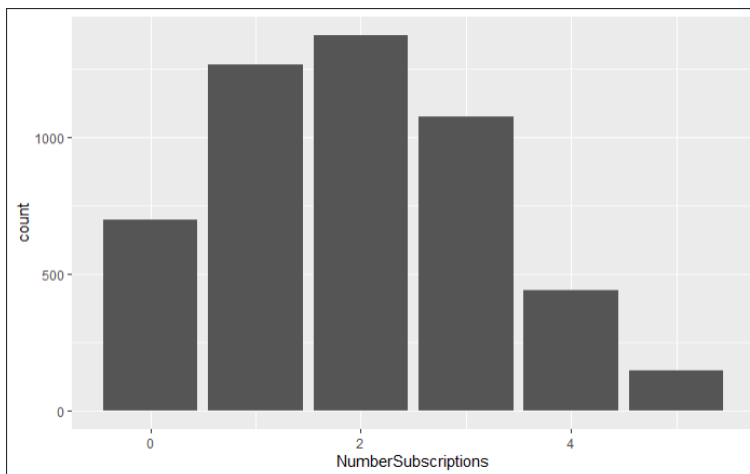


Figure 13 shows the distribution of customers across the number of plans, created in R.

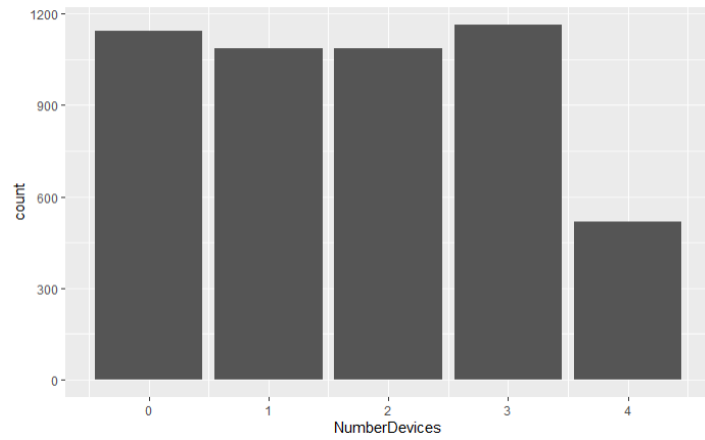


Figure 14 shows the distribution of customers across the number of devices, created in R.

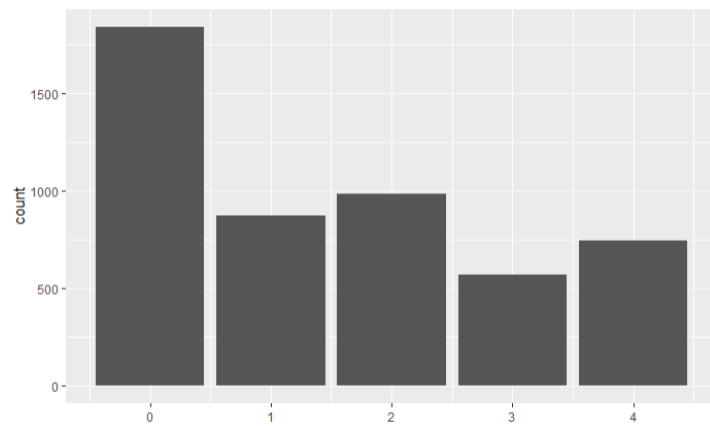


Figure 15 shows the distribution of customers across the number of devices, created in R.

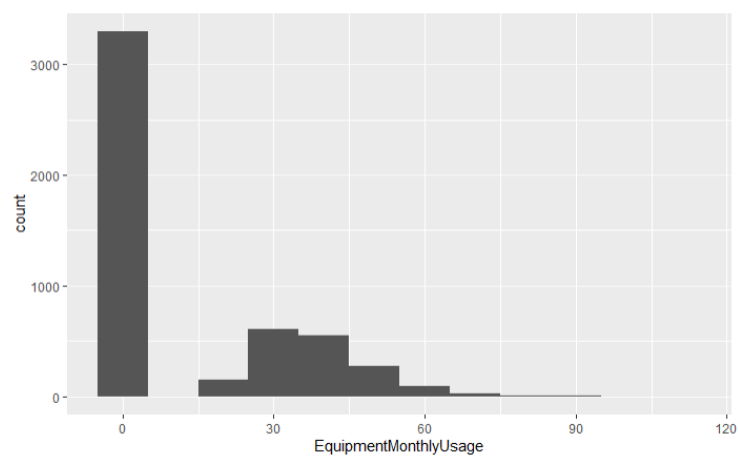


Figure 16 shows the distribution of customers based on monthly equipment usage, created in R.

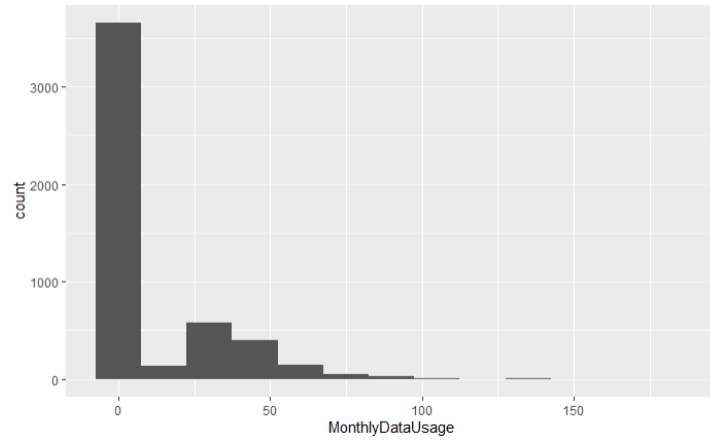


Figure 17 shows the distribution of customers based on monthly data usage, created in R.

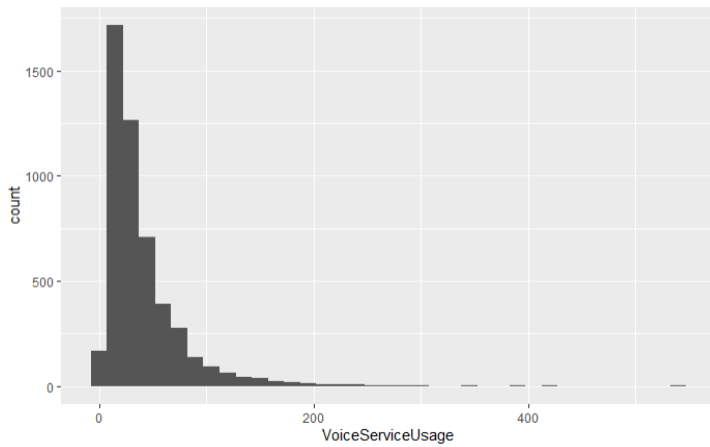


Figure 18 shows the distribution of customers based on monthly data usage, created in R.

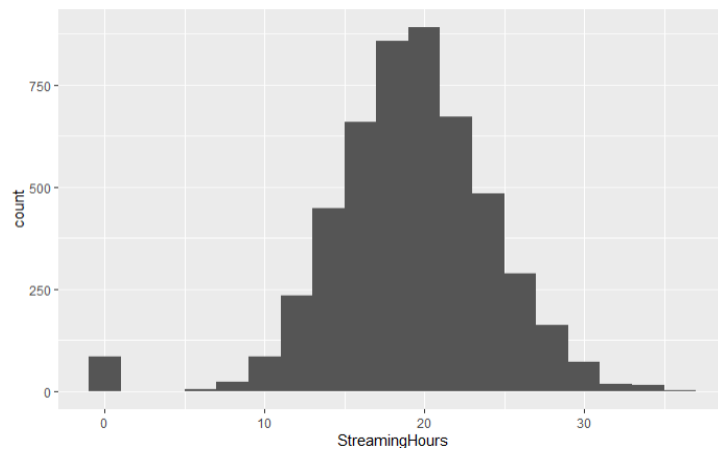


Figure 19 shows the distribution of customers based on monthly data usage, created in R.

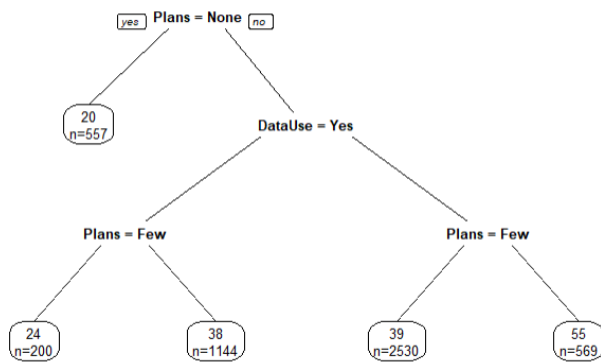


Figure 20 shows the CART tree created using provider tenure (in months) as the target variable and number of plans and data use.

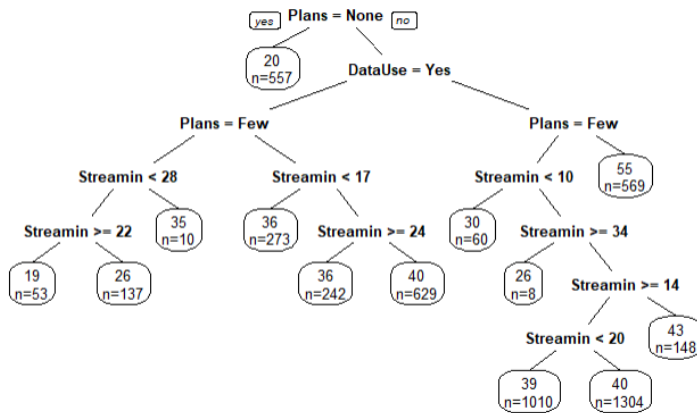


Figure 21 shows the CART tree created using provider tenure (in months) as the target variable and number of plans, streaming hours, and data use.

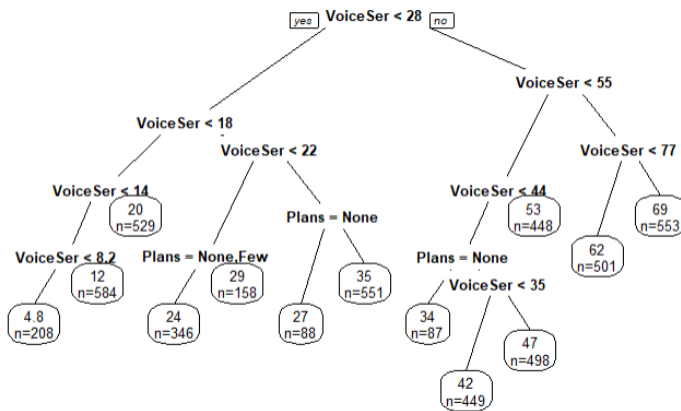


Figure 22 shows the CART tree created using provider tenure (in months) as the target variable and number of plans, streaming groups, voice service usage, and data use.

CART segments - Gender

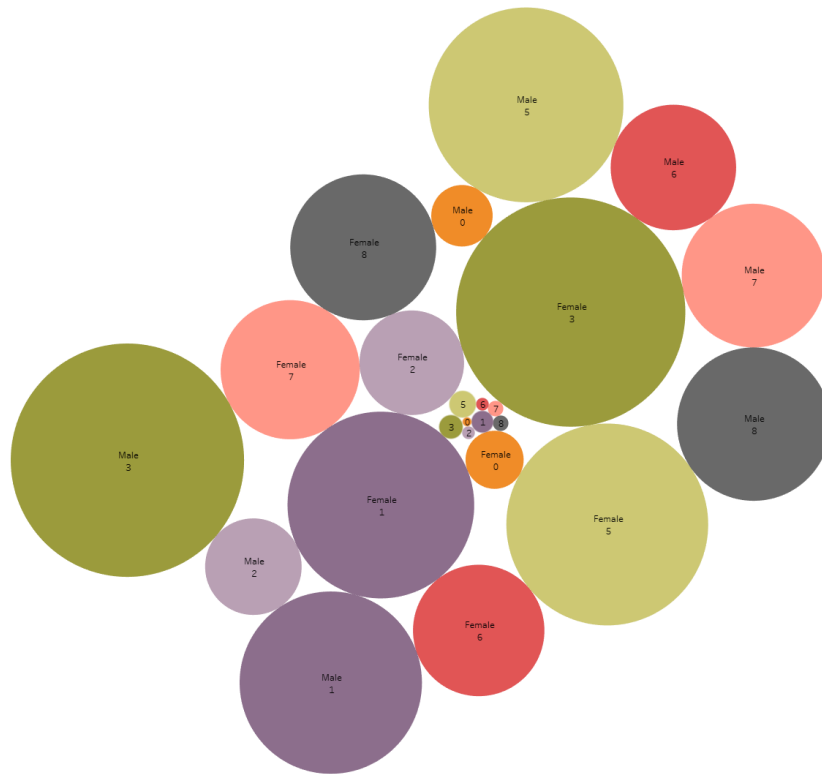


Figure 23 shows a visualization that breaks down the average provider tenure by gender across the CART tree segments; upon examination, I was able to identify segment 0, which I did not anticipate. When I returned to my R code, I was able to identify and fix a mistake in the code, reconnect the data in Tableau Prep to fix the values, and rerun the output flow to ensure the data was correct in Tableau Desktop.

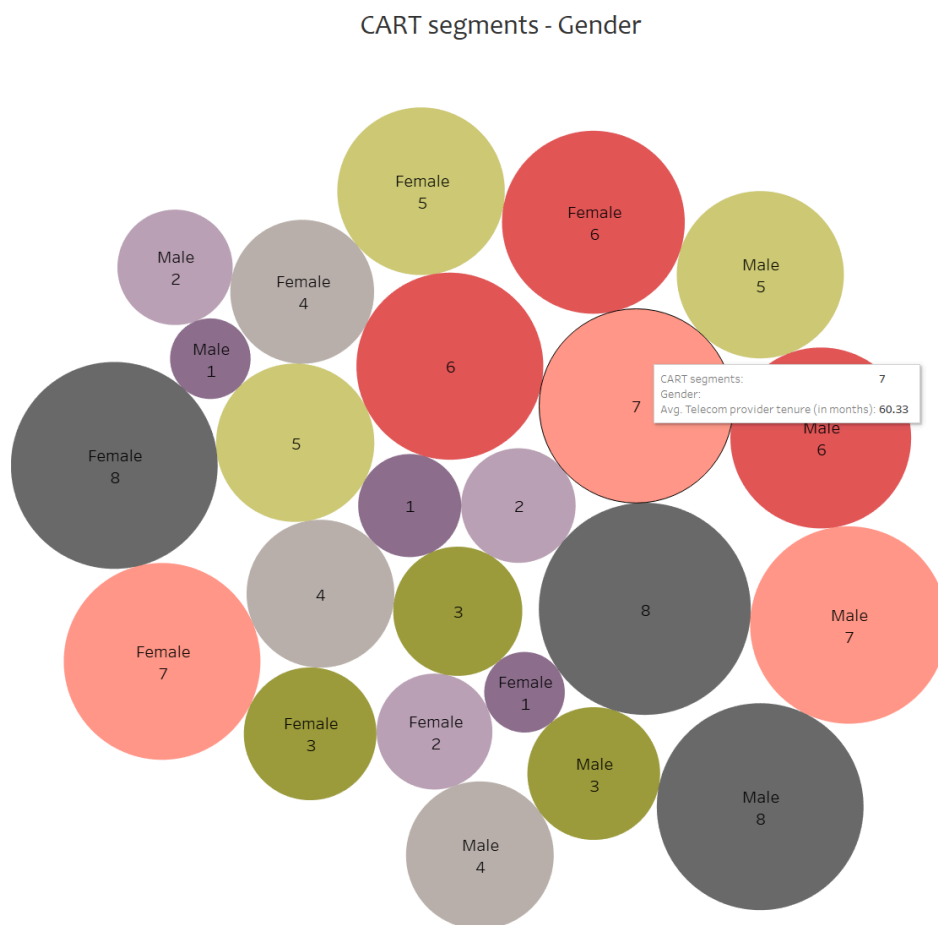


Figure 24 shows a visualization that breaks down the average provider tenure by gender across the CART tree segments.

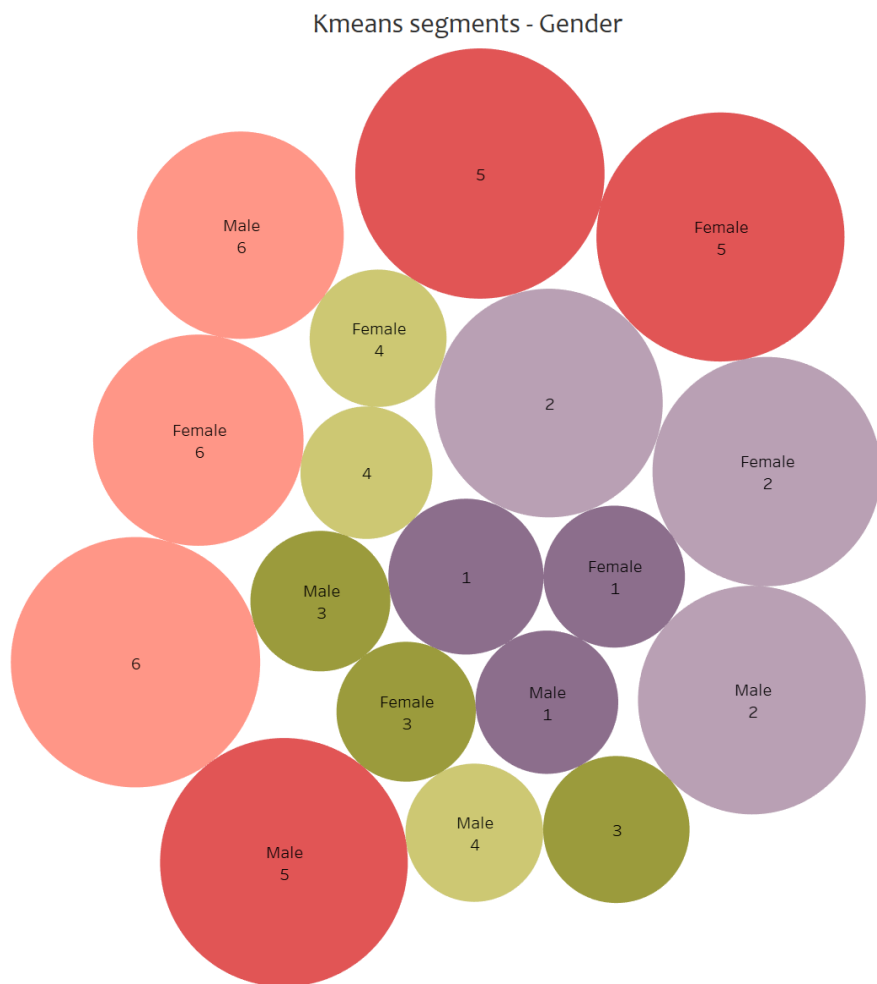


Figure 25 shows a visualization that breaks down the average provider tenure by gender across the K-means segments.

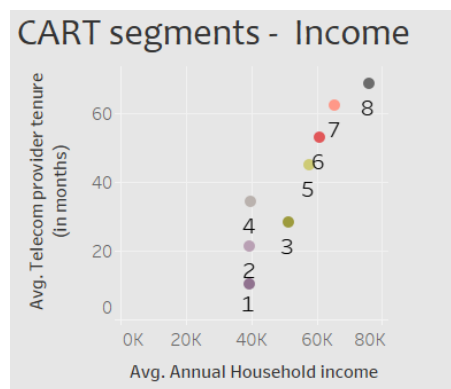


Figure 26 shows a scatterplot of average annual household income versus average provider tenure across the CART tree segments.

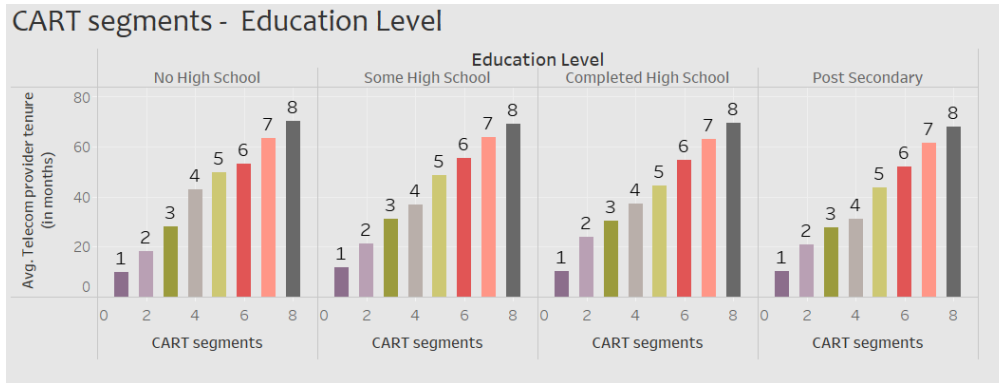


Figure 27 shows a bar graphs of the average provider tenure broken down by education level across the CART tree segments

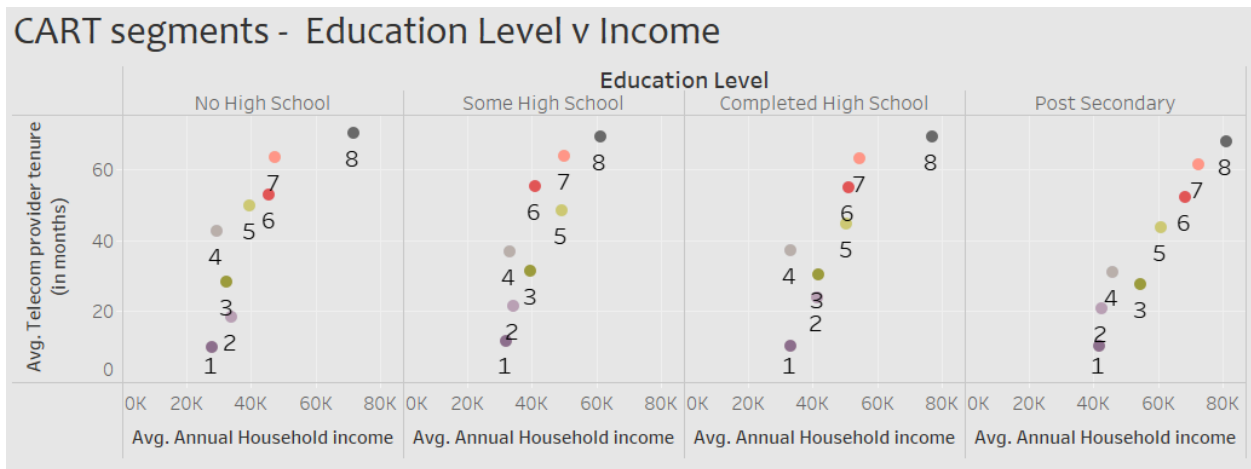


Figure 28 shows a scatterplot of average annual household income versus average provider tenure broken down by education level across the CART tree segments.

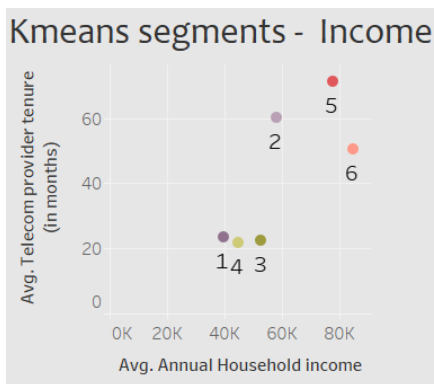


Figure 29 shows a scatterplot of average annual household income versus average provider tenure across the K-means segments.

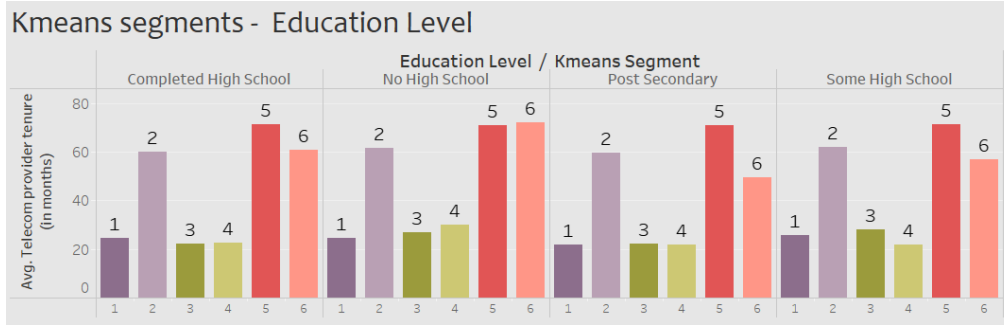


Figure 30 shows a bar graphs of the average provider tenure broken down by education level across the CART tree segments

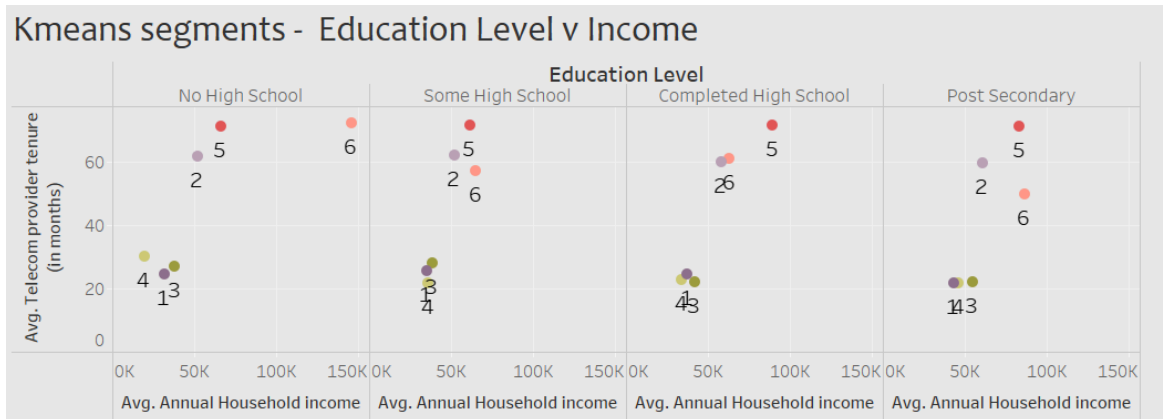


Figure 31 shows a scatterplot of average annual household income versus average provider tenure broken down by education level across the K-means segments.

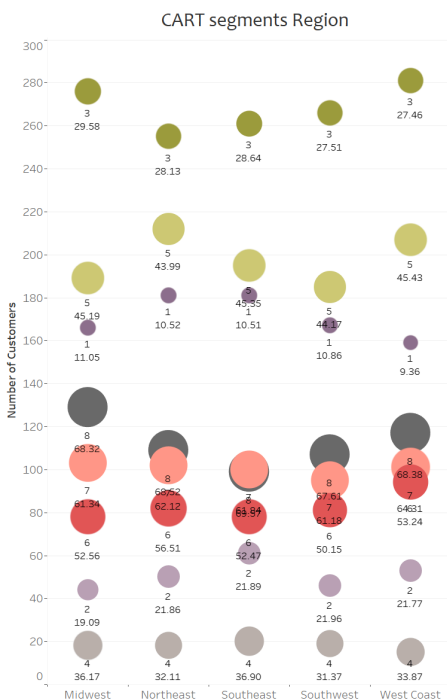


Figure 32 shows the number of customers in each region across CART tree segments where the size and label correspond to average provider tenure.

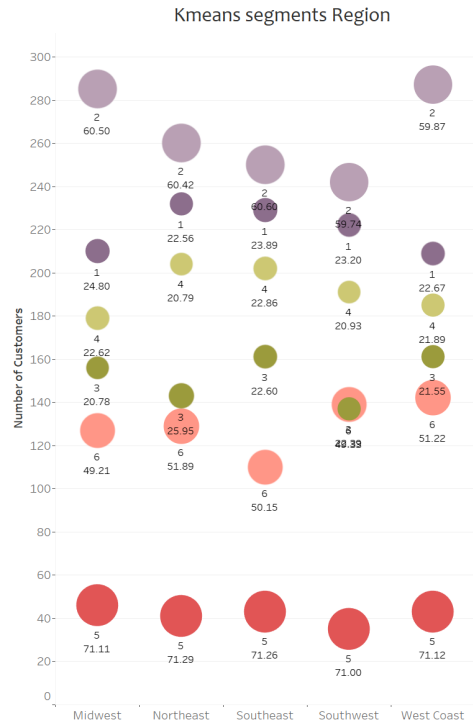


Figure 33 shows the number of customers in each region across K-means segments where the size and label correspond to average provider tenure.

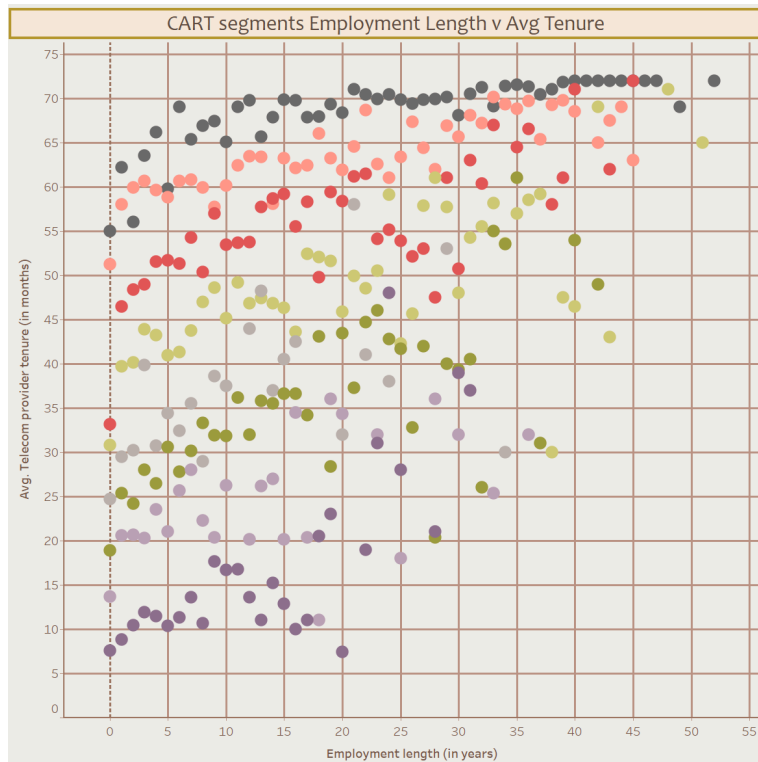


Figure 34 shows the employment length in years versus the average provider tenure across CART tree segments.

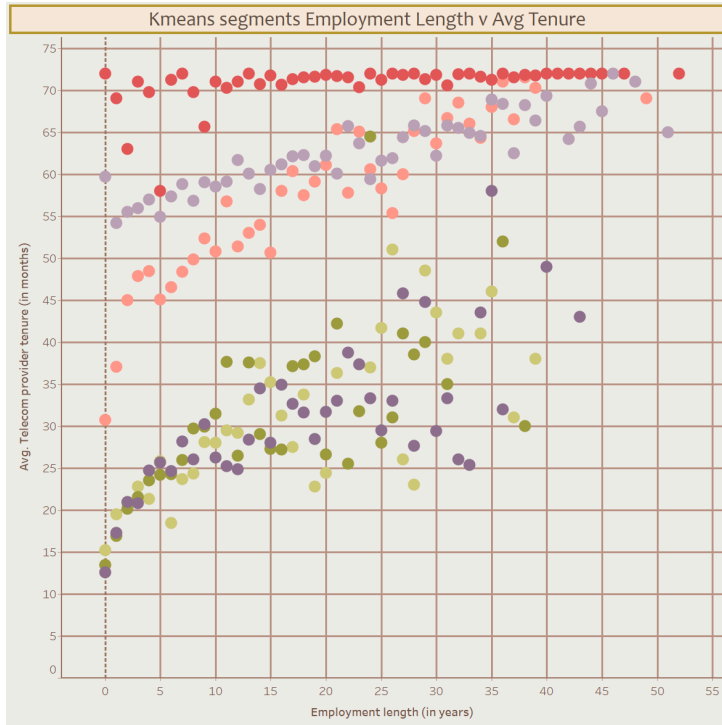


Figure 35 shows the employment length in years versus the average provider tenure across K-means segments.

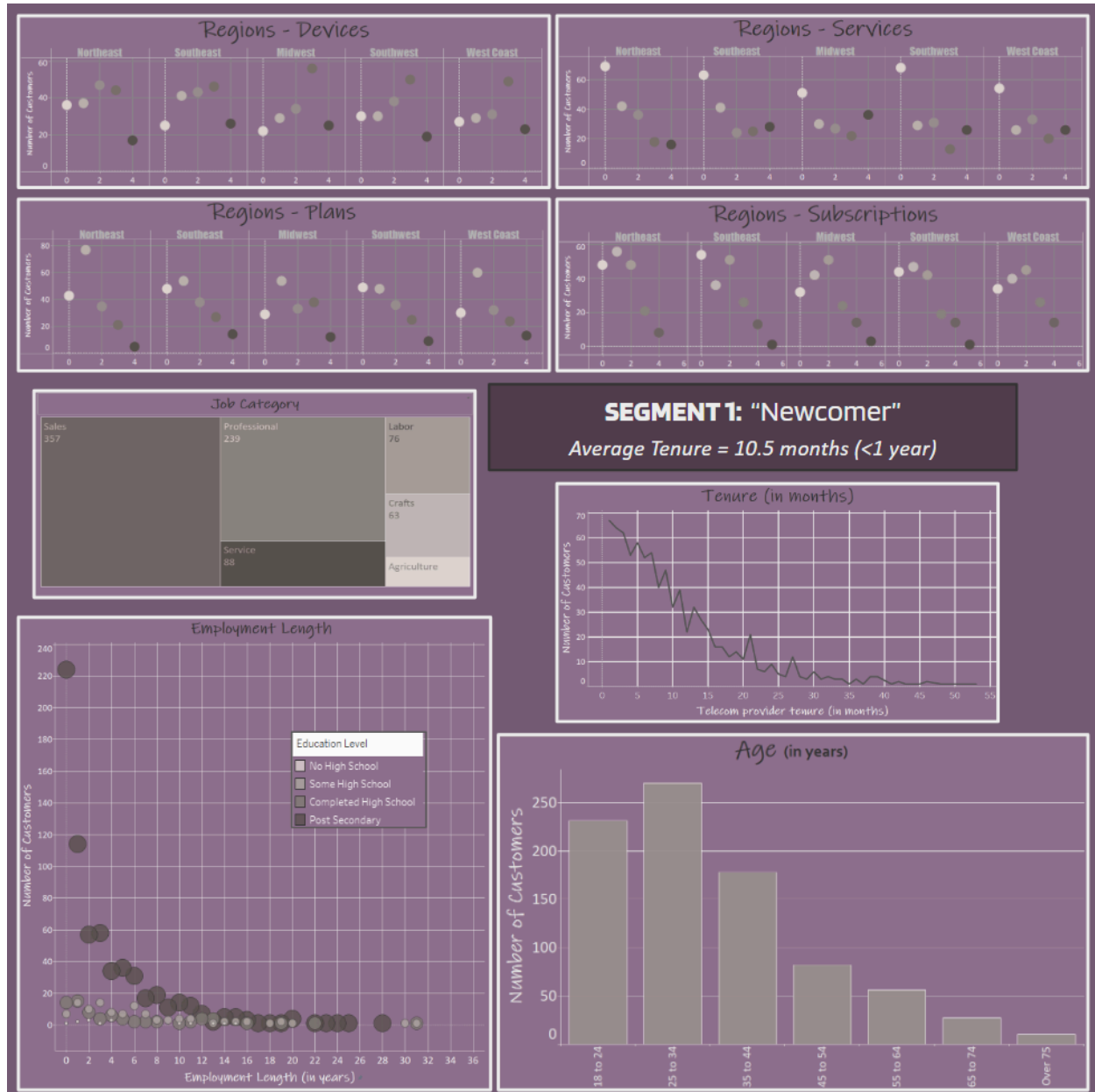


Figure 36 shows the customer profile for Segment 1: "Newcomer".



Figure 37 shows the customer profile for Segment 2: "Emerging High Risk".

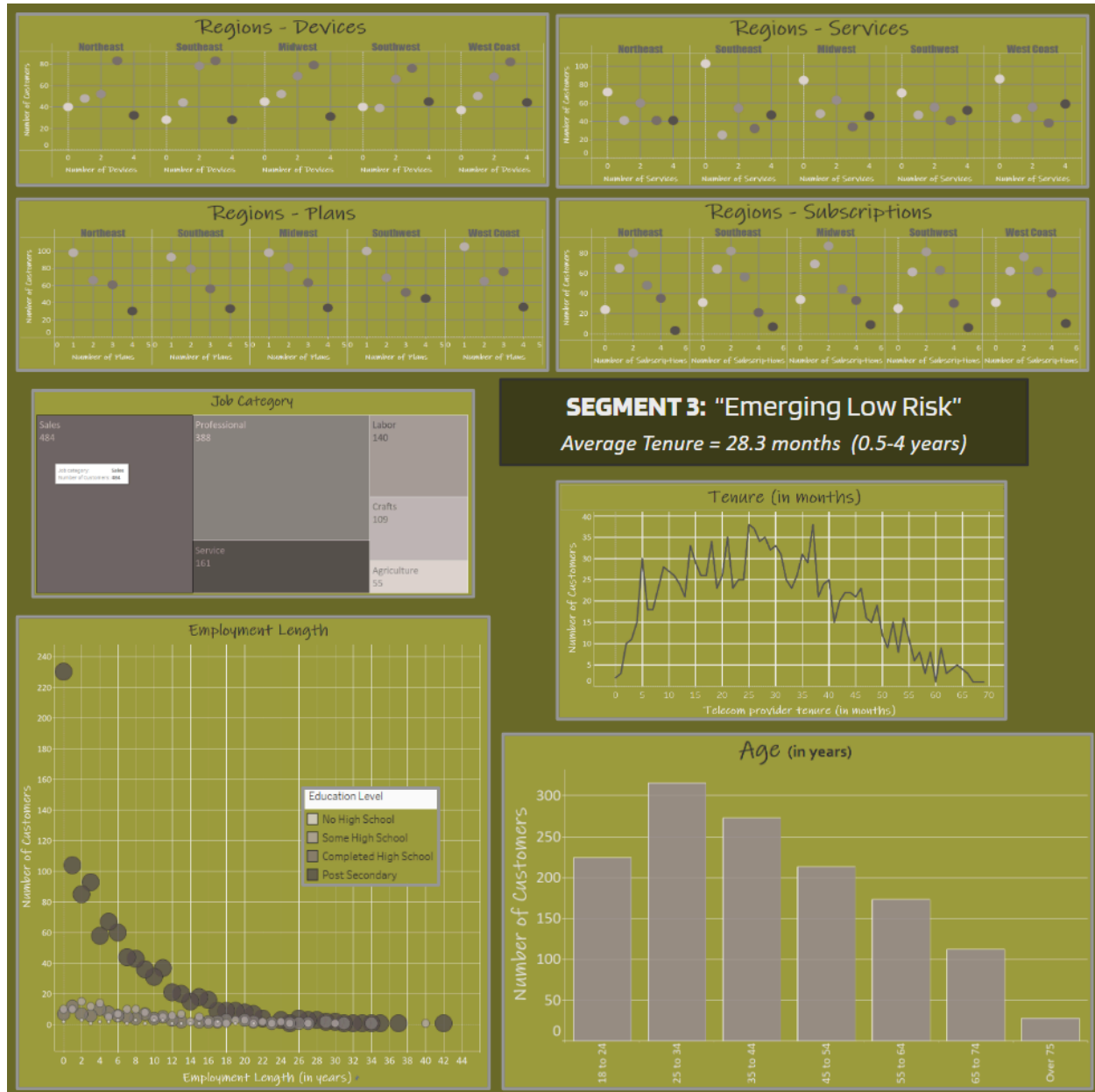


Figure 38 shows the customer profile for Segment 3: "Emerging Low Risk".

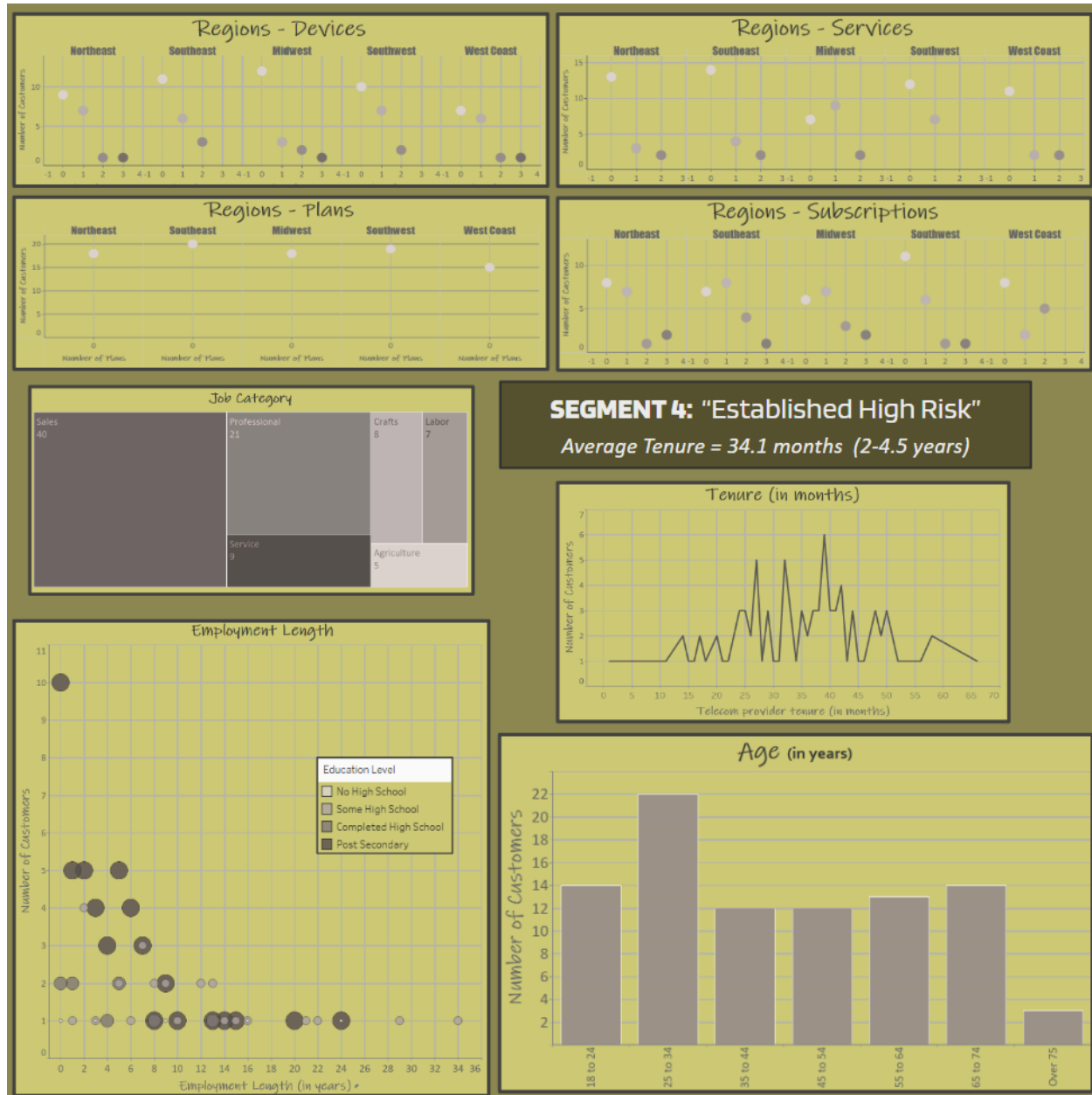


Figure 39 shows the customer profile for Segment 4: "Established High Risk".

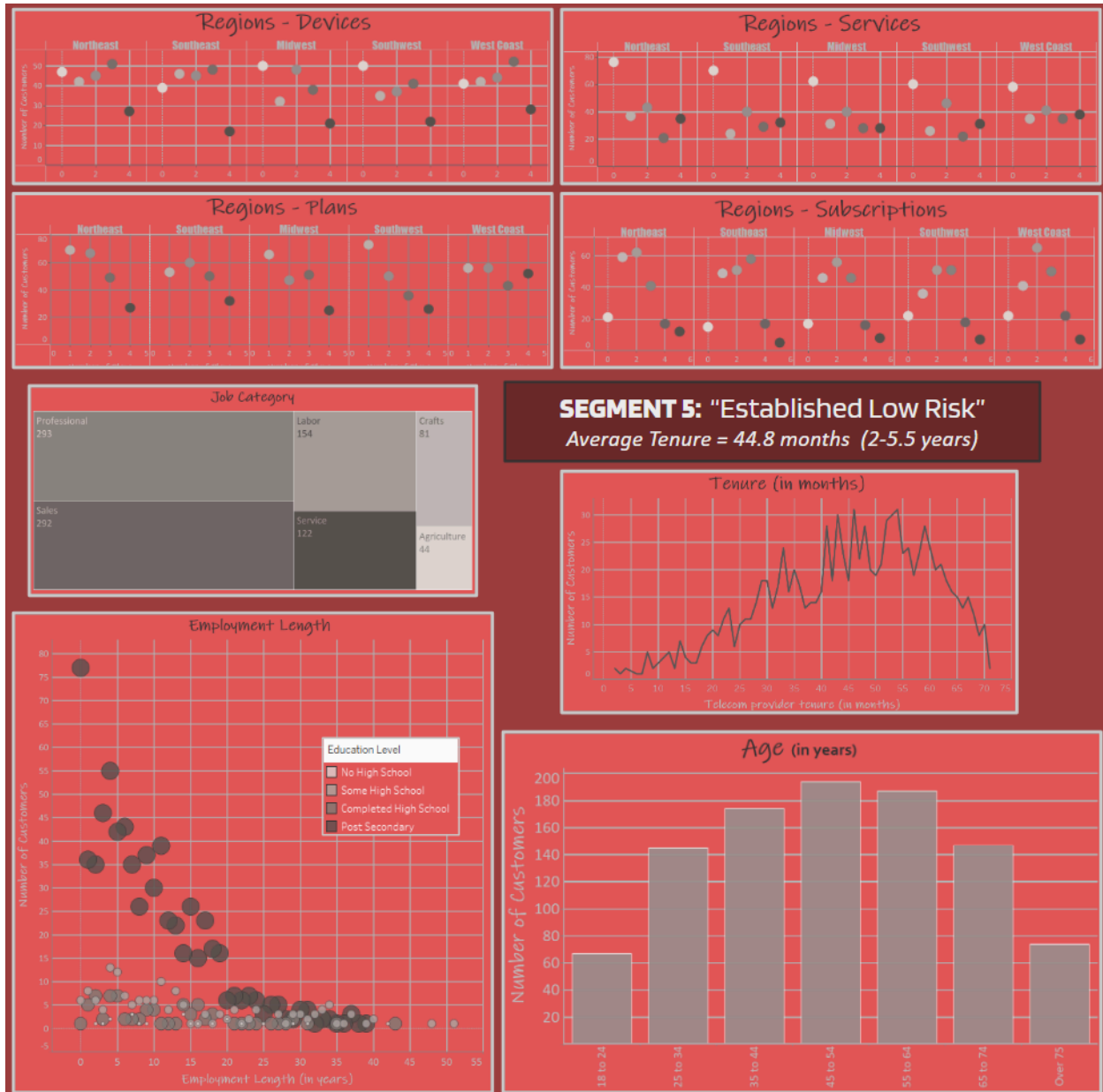


Figure 40 shows the customer profile for Segment 5: "Established Low Risk".

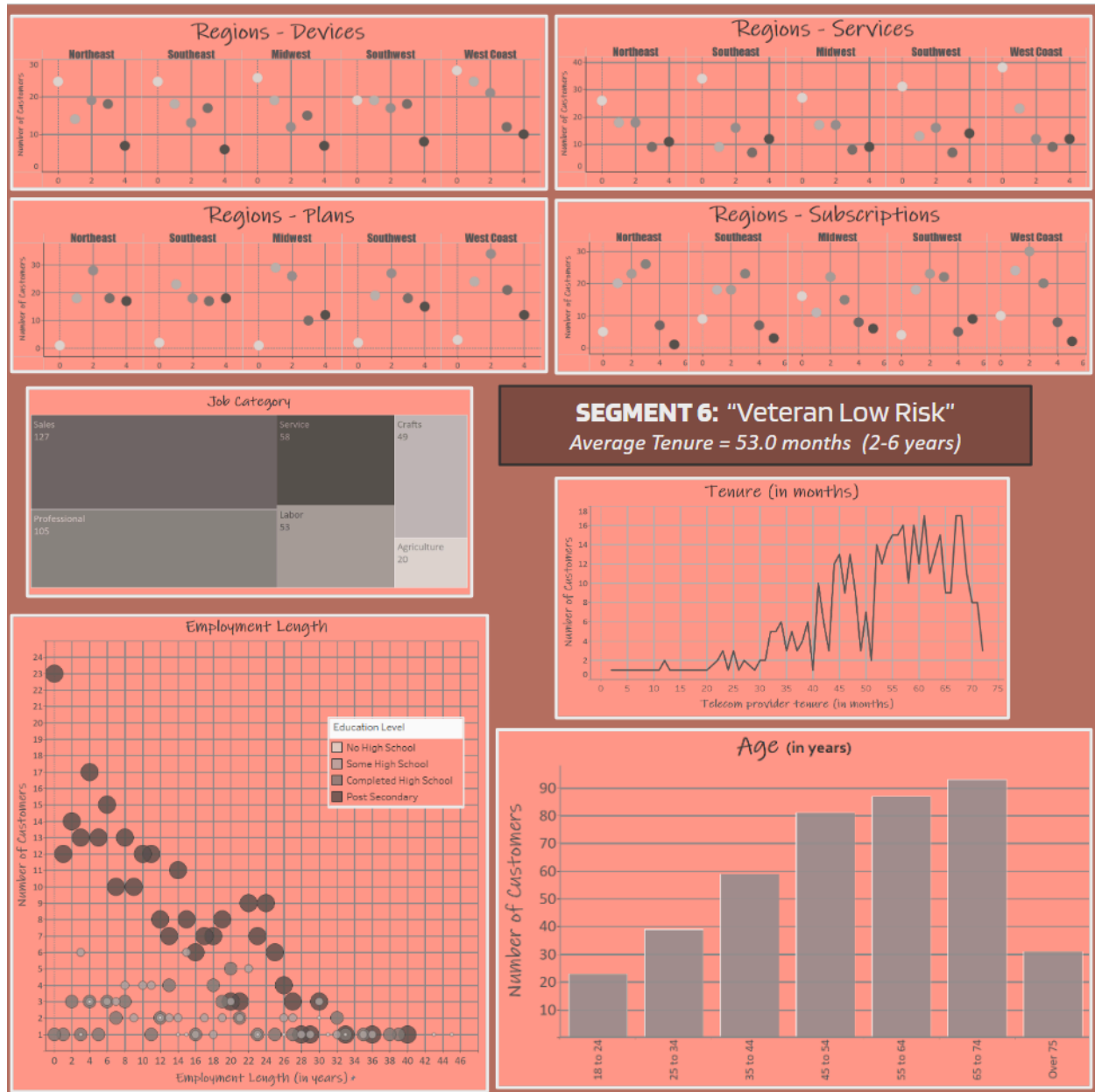


Figure 41 shows the customer profile for Segment 6: "Veteran Low Risk".

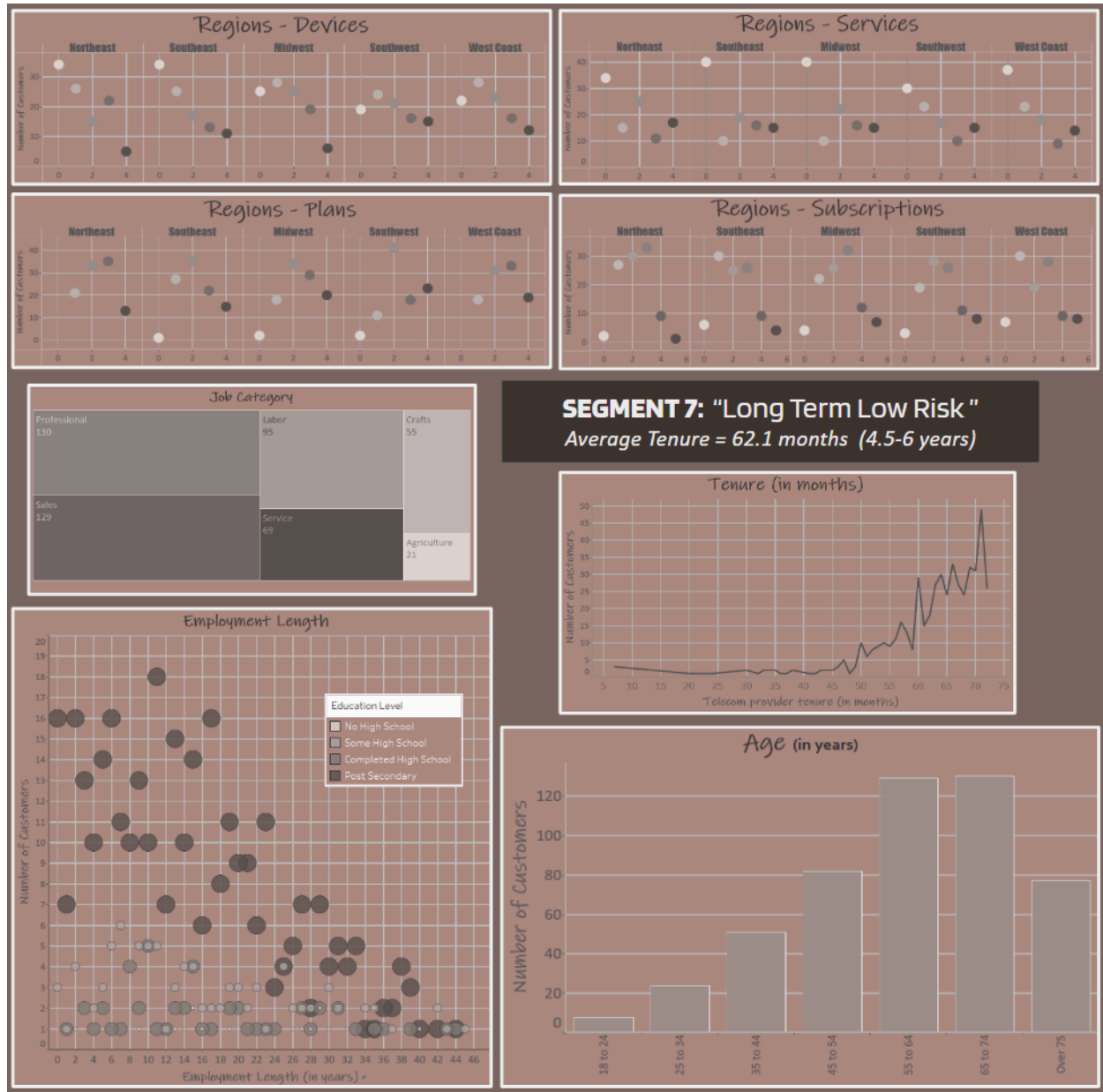


Figure 42 shows the customer profile for Segment 6: "Long Term Low Risk".

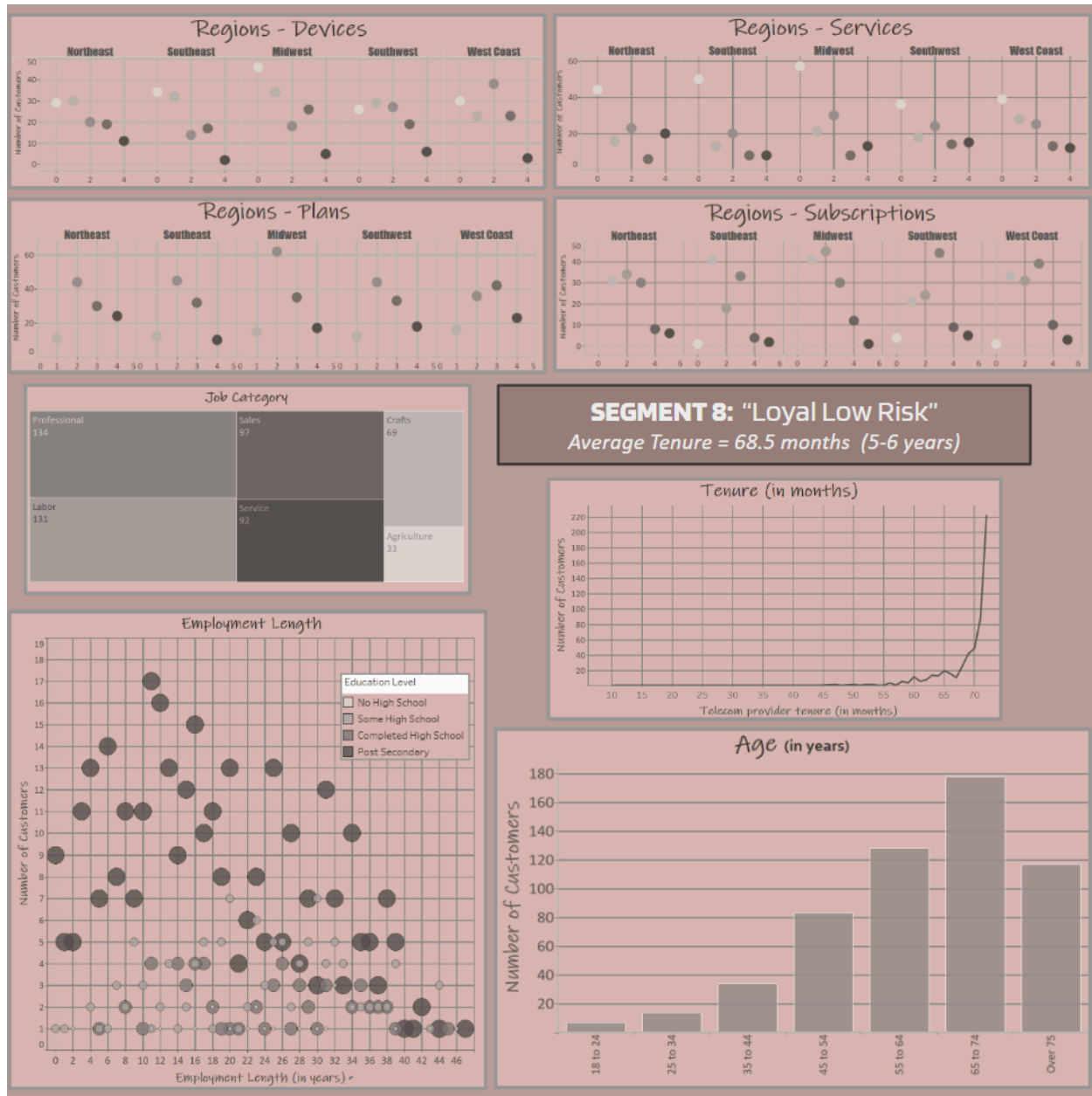


Figure 43 shows the customer profile for Segment 6: "Long Term Low Risk".