Part I: Research Question

A. Describe the purpose of this data mining report by doing the following:

1. Propose one question relevant to a real-world organizational situation that you will answer by using principal component analysis (PCA).

A principal component analysis can provide valuable insight into the variance within a data set and which features have the most significant impact on that variance. This understanding reduces the number of dimensions of a data set, making further analysis more efficient.

For this analysis of the churn data set, can a PCA identify the number of features that account for the greatest variance in this data set and their relationships to continuous variables?

2. Define one goal of the data analysis. Ensure that your goal is reasonable within the scope of the scenario and is represented in the available data.

Performing this principal component analysis will help identify the data set's principal components. This analysis aims to establish how many principal components to keep while still accounting for the largest amount of variance.

Part II: Method Justification

B. Explain the reasons for using PCA by doing the following:

1. Explain how PCA analyzes the selected data set. Include expected outcomes.

A principal component analysis is a valuable tool in reducing the dimensions of a data set to allow for more efficient modeling and predictive functions to be performed.

Decorrelation is the first step of a PCA, which fits and transforms the data so that the samples align with the axes by rotating them and then shifting each so that they have a mean of zero. This transformation of the data removes any correlation between features of the data. With each sample aligned to its axes and shifted to a mean zero, variance and linear correlation can be measured with a Pearson correlation, measured between -1 and 1, with values near zero identified as having no linear correlation and larger values having strong linear correlation.

The direction of variance for each sample identifies the component, with the principal components having the most variance. A successful PCA will have identified the principal components of the dataset and the amount of explained variance of each feature. The PCA can then be used to reduce the number of components of a dataset to just those with the highest explained variance.

2. Summarize one assumption of PCA.

PCA looks for variance within the features of the data. It assumes that low variance features can be removed as noise, while high variance features are more informative.

In [160]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from scipy.stats import pearsonr
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline


%matplotlib inline
```

In [161]:
```
df = pd.read_csv('churn_clean.csv')
```

In [162]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 50 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   CaseOrder             10000 non-null  int64  
 1   Customer_id           10000 non-null  object 
 2   Interaction           10000 non-null  object 
 3   UID                   10000 non-null  object 
 4   City                  10000 non-null  object 
 5   State                 10000 non-null  object 
 6   County                10000 non-null  object 
 7   Zip                   10000 non-null  int64  
 8   Lat                   10000 non-null  float64
 9   Lng                   10000 non-null  float64
 10  Population            10000 non-null  int64  
 11  Area                  10000 non-null  object 
 12  TimeZone              10000 non-null  object 
 13  Job                   10000 non-null  object 
 14  Children              10000 non-null  int64  
 15  Age                   10000 non-null  int64  
 16  Income                10000 non-null  float64
 17  Marital               10000 non-null  object 
 18  Gender                10000 non-null  object 
 19  Churn                 10000 non-null  object 
 20  Outage_sec_perweek    10000 non-null  float64
 21  Email                 10000 non-null  int64  
 22  Contacts              10000 non-null  int64  
 23  Yearly_equip_failure  10000 non-null  int64  
 24  Techie                10000 non-null  object 
 25  Contract              10000 non-null  object 
 26  Port_modem            10000 non-null  object 
 27  Tablet                10000 non-null  object 
 28  InternetService       10000 non-null  object 
 29  Phone                 10000 non-null  object 
 30  Multiple              10000 non-null  object 
 31  OnlineSecurity        10000 non-null  object 
 32  OnlineBackup          10000 non-null  object 
 33  DeviceProtection      10000 non-null  object 
 34  TechSupport           10000 non-null  object 
 35  StreamingTV           10000 non-null  object 
 36  StreamingMovies       10000 non-null  object 
 37  PaperlessBilling      10000 non-null  object 
 38  PaymentMethod         10000 non-null  object 
 39  Tenure                10000 non-null  float64
 40  MonthlyCharge         10000 non-null  float64
 41  Bandwidth_GB_Year     10000 non-null  float64
 42  Item1                 10000 non-null  int64  
 43  Item2                 10000 non-null  int64  
 44  Item3                 10000 non-null  int64  
 45  Item4                 10000 non-null  int64  
 46  Item5                 10000 non-null  int64  
 47  Item6                 10000 non-null  int64  
 48  Item7                 10000 non-null  int64  
 49  Item8                 10000 non-null  int64  
dtypes: float64(7), int64(16), object(27)
memory usage: 3.8+ MB
```

In [163]:
```
df.describe()
```

Out[163]:

	CaseOrder	Zip	Lat	Lng	Population	Children	
count	10000.00000	10000.000000	10000.000000	10000.000000	10000.000000	10000.0000	10000
mean	5000.50000	49153.319600	38.757567	-90.782536	9756.562400	2.0877	53
std	2886.89568	27532.196108	5.437389	15.156142	14432.698671	2.1472	20
min	1.00000	601.000000	17.966120	-171.688150	0.000000	0.0000	18
25%	2500.75000	26292.500000	35.341828	-97.082813	738.000000	0.0000	35
50%	5000.50000	48869.500000	39.395800	-87.918800	2910.500000	1.0000	53
75%	7500.25000	71866.500000	42.106908	-80.088745	13168.000000	3.0000	71
max	10000.00000	99929.000000	70.640660	-65.667850	111850.000000	10.0000	89

8 rows × 23 columns

In [164]:
```
cont_df = df.select_dtypes(include=[np.number])
cont_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 23 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   CaseOrder             10000 non-null  int64  
 1   Zip                   10000 non-null  int64  
 2   Lat                   10000 non-null  float64
 3   Lng                   10000 non-null  float64
 4   Population            10000 non-null  int64  
 5   Children              10000 non-null  int64  
 6   Age                   10000 non-null  int64  
 7   Income                10000 non-null  float64
 8   Outage_sec_perweek    10000 non-null  float64
 9   Email                 10000 non-null  int64  
 10  Contacts              10000 non-null  int64  
 11  Yearly_equip_failure  10000 non-null  int64  
 12  Tenure                10000 non-null  float64
 13  MonthlyCharge         10000 non-null  float64
 14  Bandwidth_GB_Year     10000 non-null  float64
 15  Item1                 10000 non-null  int64  
 16  Item2                 10000 non-null  int64  
 17  Item3                 10000 non-null  int64  
 18  Item4                 10000 non-null  int64  
 19  Item5                 10000 non-null  int64  
 20  Item6                 10000 non-null  int64  
 21  Item7                 10000 non-null  int64  
 22  Item8                 10000 non-null  int64  
dtypes: float64(7), int64(16)
memory usage: 1.8 MB
```

In [165]:
```python
data = cont_df.drop(columns=['CaseOrder', 'Zip','Item1', 'Item2', 'Item3',
                             'Item4', 'Item5', 'Item6', 'Item7', 'Item8'])
```

In [166]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Lat                   10000 non-null  float64
 1   Lng                   10000 non-null  float64
 2   Population            10000 non-null  int64  
 3   Children              10000 non-null  int64  
 4   Age                   10000 non-null  int64  
 5   Income                10000 non-null  float64
 6   Outage_sec_perweek    10000 non-null  float64
 7   Email                 10000 non-null  int64  
 8   Contacts              10000 non-null  int64  
 9   Yearly_equip_failure  10000 non-null  int64  
 10  Tenure                10000 non-null  float64
 11  MonthlyCharge         10000 non-null  float64
 12  Bandwidth_GB_Year     10000 non-null  float64
dtypes: float64(7), int64(6)
memory usage: 1015.8 KB
```

In [167]:
```python
data.columns
```

Out[167]:
```
Index(['Lat', 'Lng', 'Population', 'Children', 'Age', 'Income',
       'Outage_sec_perweek', 'Email', 'Contacts', 'Yearly_equip_failure',
       'Tenure', 'MonthlyCharge', 'Bandwidth_GB_Year'],
      dtype='object')
```

In [184]:
```python
data.describe()
```

Out[184]:

	Lat	Lng	Population	Children	Age	Income	Out
count	10000.000000	10000.000000	10000.000000	10000.0000	10000.000000	10000.000000	
mean	38.757567	-90.782536	9756.562400	2.0877	53.078400	39806.926771	
std	5.437389	15.156142	14432.698671	2.1472	20.698882	28199.916702	
min	17.966120	-171.688150	0.000000	0.0000	18.000000	348.670000	
25%	35.341828	-97.082813	738.000000	0.0000	35.000000	19224.717500	
50%	39.395800	-87.918800	2910.500000	1.0000	53.000000	33170.605000	
75%	42.106908	-80.088745	13168.000000	3.0000	71.000000	53246.170000	
max	70.640660	-65.667850	111850.000000	10.0000	89.000000	258900.700000	

1. Identify the continuous dataset variables that you will need in order to answer the PCA question proposed in part A1.

This dataset has 50 variables with 23 numerical variables.

Of the 23 numerical variables, the following are numerical but not continuous variables and can be excluded:

- CaseOrder
- Zip
- Item1
- Item2
- Item3
- Item4
- Item5
- Item6
- Item7
- Item8

The remaining 13 variables are continuous and can be used in the PCA. These include:

- Lat
- Lng
- Population
- Children
- Age
- Income
- Outage_sec_perweek
- Email
- Contacts
- Yearly_equip_failure
- Tenure
- MonthlyCharge
- Bandwidth_GB_Year

2. Standardize the continuous dataset variables identified in part C1. Include a copy of the cleaned dataset.

In [200]:
```
scaler = StandardScaler()
scaled = scaler.fit_transform(data)
```

In [201]:
```
data.to_csv("selected_variables_D212_Task2.csv")
pd.DataFrame(scaled).to_csv("scaled_and_transformed_data_D212_Task2.csv")
```

Part IV: Analysis

D. Perform PCA by doing the following:

1. Determine the matrix of all the principal components.

In [202]:
```
pca = PCA()
transformed = pca.fit_transform(scaled)
```

In [203]:
```
cols = []
i=1

while i <= len(pca.components_):
    cols.append("PC " + str(i))
    i = i + 1

loadings = pd.DataFrame(pca.components_, columns = cols, index=data.columns)
loadings
```

Out[203]:

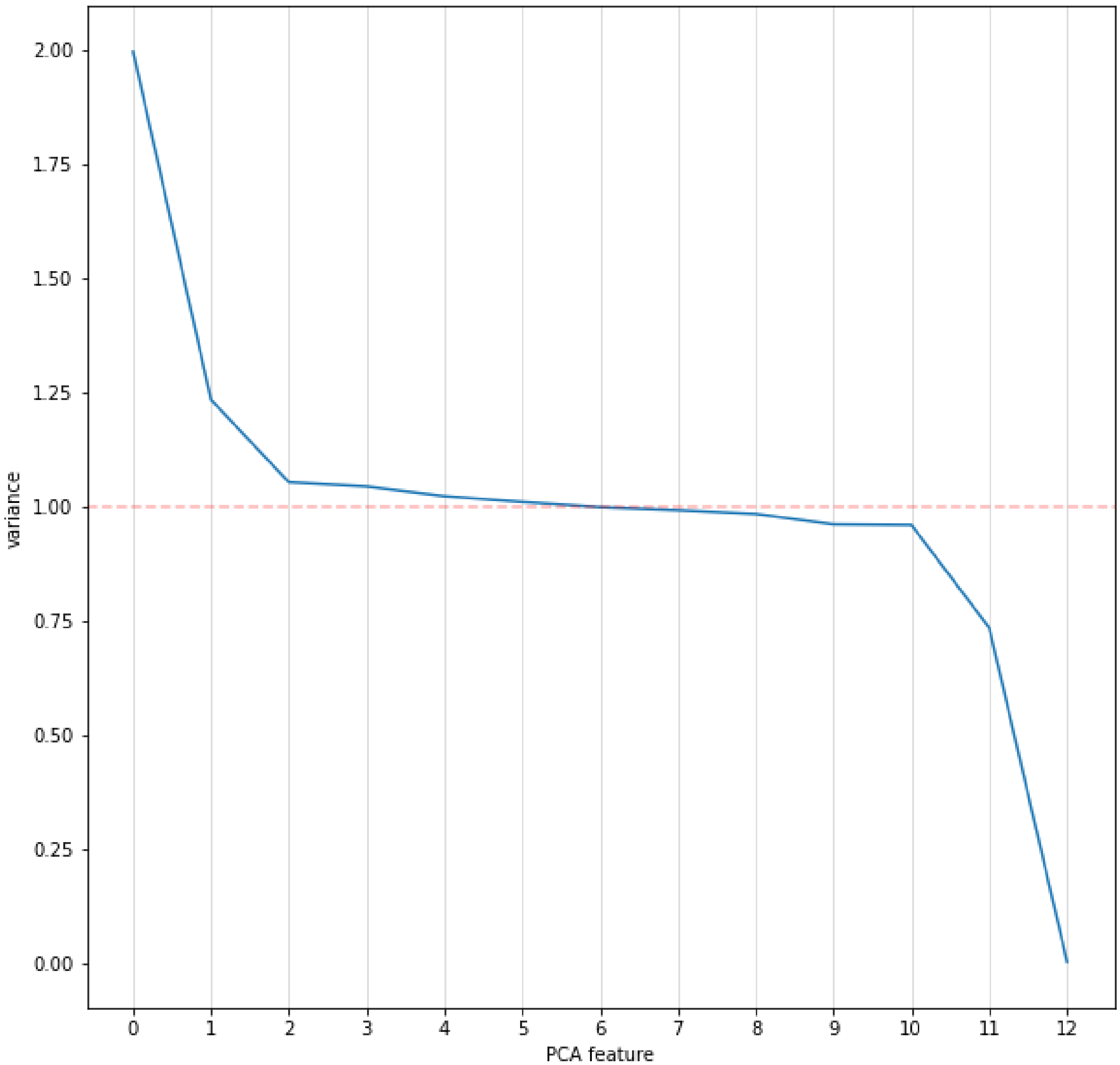
	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7
Lat	-0.023161	0.007911	-0.001230	0.014244	0.001860	0.004185	0.005811
Lng	-0.714010	0.180879	0.653439	-0.014267	0.052795	-0.054602	0.009174
Population	-0.031715	-0.285753	0.151916	0.447882	-0.443537	0.195742	-0.249550
Children	0.109414	-0.736871	0.322012	-0.464670	0.227235	-0.041772	-0.126214
Age	-0.094872	0.344620	-0.119517	-0.107498	0.436759	0.312779	-0.455981
Income	-0.030887	-0.087695	0.098791	0.130597	-0.096321	0.100371	0.597523
Outage_sec_perweek	-0.010719	-0.052349	0.053682	0.034812	-0.188399	0.773549	0.051915
Email	-0.020375	-0.086499	0.079161	-0.065531	0.093484	0.335467	-0.184658
Contacts	0.090273	-0.172285	-0.027392	0.192459	0.342892	0.246663	0.057056
Yearly_equip_failure	0.018619	-0.151301	0.055304	0.437471	-0.083596	-0.275852	-0.515406
Tenure	0.053958	-0.112280	0.100818	0.565626	0.614892	-0.033742	0.223304
MonthlyCharge	0.674376	0.375138	0.631729	-0.011794	-0.037729	0.006645	-0.034155
Bandwidth_GB_Year	0.001077	0.000788	-0.000070	-0.021597	0.022360	-0.000941	0.000271

2. Identify the total number of principal components using the elbow rule or the Kaiser criterion. Include a screenshot of the scree plot.

In [204]:

```
plt.figure(figsize=(10,10))

features = range(pca.n_components_)
plt.plot(features, pca.explained_variance_)
plt.grid(axis='x',alpha=.5)
plt.axhline(y=1, color='r', linestyle='--',alpha=.3)
plt.xlabel('PCA feature')
plt.ylabel('variance')
plt.xticks(features)
plt.show();
```



In [205]:
```
variance = pd.DataFrame(pca.explained_variance_, columns = ['Explained Varianc
e'], index=cols)
variance['Ratio'] = pca.explained_variance_ratio_
variance['Ratio Percentage'] = (variance['Ratio']*100).round(2).astype(str) +
'%'
variance['Ratio Cumulative Sum'] = pca.explained_variance_ratio_.cumsum()
variance['Ratio Cumulative Sum Percentage'] = (variance['Ratio Cumulative Sum'
]*100).round(2).astype(str) + '%'
variance
```

Out[205]:

	Explained Variance	Ratio	Ratio Percentage	Ratio Cumulative Sum	Ratio Cumulative Sum Percentage
PC 1	1.994905	0.153439	15.34%	0.153439	15.34%
PC 2	1.234151	0.094925	9.49%	0.248364	24.84%
PC 3	1.053770	0.081051	8.11%	0.329415	32.94%
PC 4	1.044695	0.080353	8.04%	0.409768	40.98%
PC 5	1.023288	0.078707	7.87%	0.488475	48.85%
PC 6	1.010782	0.077745	7.77%	0.566220	56.62%
PC 7	0.999303	0.076862	7.69%	0.643081	64.31%
PC 8	0.992675	0.076352	7.64%	0.719433	71.94%
PC 9	0.984531	0.075726	7.57%	0.795159	79.52%
PC 10	0.961886	0.073984	7.4%	0.869143	86.91%
PC 11	0.960495	0.073877	7.39%	0.943020	94.3%
PC 12	0.735353	0.056560	5.66%	0.999580	99.96%
PC 13	0.005466	0.000420	0.04%	1.000000	100.0%

2. Identify the total number of principal components using the elbow rule or the Kaiser criterion. Include a screenshot of the scree plot.

Using the Kaiser Criterion, principal components with an explained variance over 1.0 can be selected for the PCA. This would include the first 6 Principal Components.

In [228]:
```
scaler = StandardScaler()
pca = PCA(n_components=6)
pipeline = make_pipeline(scaler, pca)
transformed = pipeline.fit_transform(data)
```

In [234]:
```
print(pca.explained_variance_)
```

```
[1.99490495 1.23415146 1.05376978 1.04469451 1.02328808 1.01078182]
```

In [235]:
```
print(pca.explained_variance_ratio_)
```

```
[0.15343888 0.09492523 0.08105111 0.08035308 0.0787066  0.07774467]
```

In [236]:
```
print(pca.explained_variance_ratio_.cumsum())
```

```
[0.15343888 0.24836412 0.32941522 0.4097683  0.4884749  0.56621957]
```

3. Identify the variance of each of the principal components identified in part D2.

In [238]:
```
cols = []
i=1

while i <= len(pca.components_):
    cols.append("PC " + str(i))
    i = i + 1

variance = pd.DataFrame(pca.explained_variance_, columns = ['Explained Varianc
e'], index=cols)
variance['Ratio'] = pca.explained_variance_ratio_
variance['Percentage'] = (variance['Ratio']*100).round(2).astype(str) + '%'
variance['Ratio Cumulative Sum'] = pca.explained_variance_ratio_.cumsum()
variance['Ratio Cumulative Sum Percentage'] = (variance['Ratio Cumulative Sum'
]*100).round(2).astype(str) + '%'
variance
```

Out[238]:

	Explained Variance	Ratio	Percentage	Ratio Cumulative Sum	Ratio Cumulative Sum Percentage
PC 1	1.994905	0.153439	15.34%	0.153439	15.34%
PC 2	1.234151	0.094925	9.49%	0.248364	24.84%
PC 3	1.053770	0.081051	8.11%	0.329415	32.94%
PC 4	1.044695	0.080353	8.04%	0.409768	40.98%
PC 5	1.023288	0.078707	7.87%	0.488475	48.85%
PC 6	1.010782	0.077745	7.77%	0.566220	56.62%

4. Identify the total variance captured by the principal components identified in part D2.

In [241]:
```
print('The total variance for the identified 6 Principal Compenents is: ', var
iance['Explained Variance'].sum())
print('The total ratio of explained varience of the identified 6 Principal Com
penents is: ', variance['Ratio'].sum().round(4))
print('Or as a percentage: ', (variance['Ratio']*100).sum().round(2).astype(st
r) + '%')
```

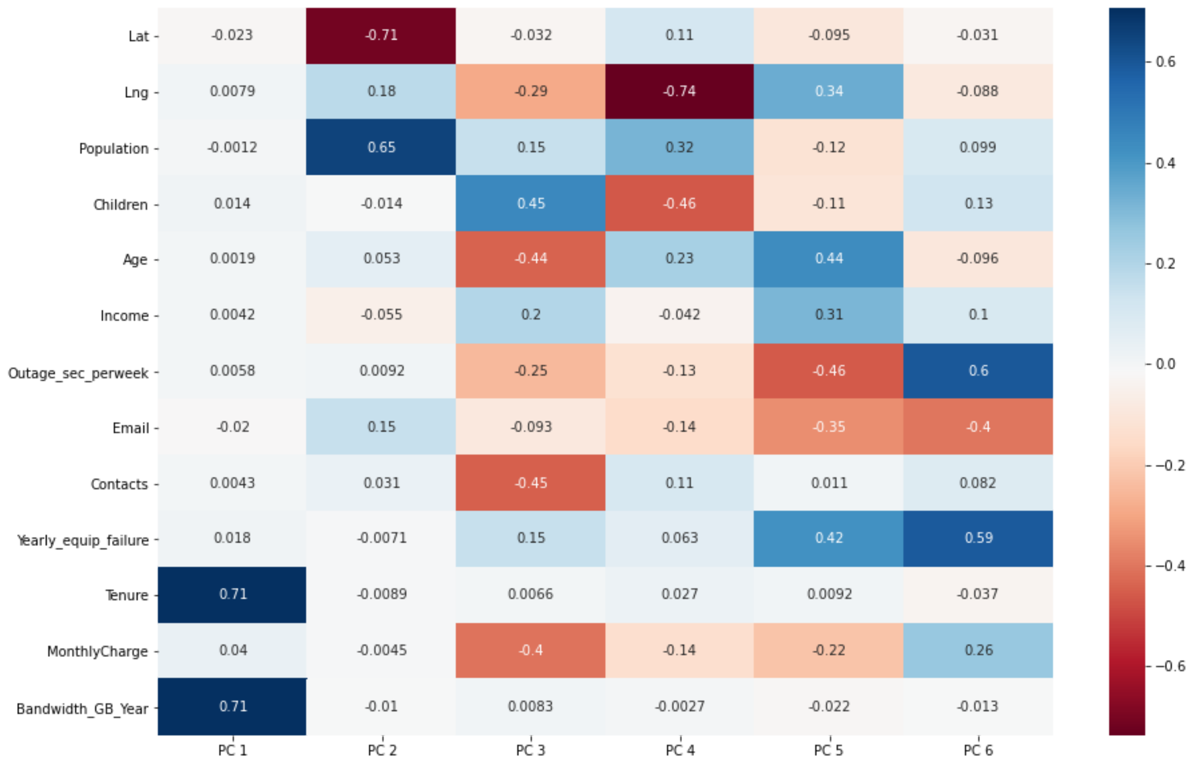
```
The total variance for the identified 6 Principal Compenents is:  7.361590597
900971
The total ratio of explained varience of the identified 6 Principal Compenent
s is:  0.5662
Or as a percentage:  56.62%
```

In [226]:
```
loadings = pd.DataFrame(pca.components_.T, columns = cols, index=data.columns)
loadings
```

Out[226]:

	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6
Lat	-0.023161	-0.714010	-0.031715	0.109414	-0.094872	-0.030887
Lng	0.007911	0.180879	-0.285753	-0.736871	0.344620	-0.087695
Population	-0.001230	0.653439	0.151916	0.322012	-0.119517	0.098791
Children	0.014244	-0.014267	0.447882	-0.464670	-0.107498	0.130597
Age	0.001860	0.052795	-0.443537	0.227235	0.436759	-0.096321
Income	0.004185	-0.054602	0.195742	-0.041772	0.312779	0.100371
Outage_sec_perweek	0.005811	0.009174	-0.249550	-0.126214	-0.455981	0.597523
Email	-0.020020	0.152355	-0.092711	-0.144998	-0.353186	-0.403463
Contacts	0.004283	0.031043	-0.447906	0.108875	0.011245	0.082442
Yearly_equip_failure	0.017665	-0.007070	0.153686	0.063449	0.420468	0.592380
Tenure	0.705211	-0.008913	0.006569	0.026652	0.009197	-0.036725
MonthlyCharge	0.040456	-0.004500	-0.404228	-0.136041	-0.218356	0.257205
Bandwidth_GB_Year	0.706719	-0.010435	0.008289	-0.002713	-0.021522	-0.012558

In [227]:
```python
plt.figure(figsize=(15,10))
sns.heatmap(loadings, cmap ='RdBu', annot = True);
```



	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6
Lat	-0.023	-0.71	-0.032	0.11	-0.095	-0.031
Lng	0.0079	0.18	-0.29	-0.74	0.34	-0.088
Population	-0.0012	0.65	0.15	0.32	-0.12	0.099
Children	0.014	-0.014	0.45	-0.46	-0.11	0.13
Age	0.0019	0.053	-0.44	0.23	0.44	-0.096
Income	0.0042	-0.055	0.2	-0.042	0.31	0.1
Outage_sec_perweek	0.0058	0.0092	-0.25	-0.13	-0.46	0.6
Email	-0.02	0.15	-0.093	-0.14	-0.35	-0.4
Contacts	0.0043	0.031	-0.45	0.11	0.011	0.082
Yearly_equip_failure	0.018	-0.0071	0.15	0.063	0.42	0.59
Tenure	0.71	-0.0089	0.0066	0.027	0.0092	-0.037
MonthlyCharge	0.04	-0.0045	-0.4	-0.14	-0.22	0.26
Bandwidth_GB_Year	0.71	-0.01	0.0083	-0.0027	-0.022	-0.013

In [264]:
```python
print(df.shape)
print(transformed.shape)
print((((1 - (transformed.size/df.size).round(2))*100).astype(str) + '%'))
```

```
(10000, 50)
(10000, 6)
88.0%
```

5. Summarize the results of your data analysis.

This PCA has successfully reduced the dimensions of this data. The original dataset was comprised of 50 variables from 10,000 samples. The result of the PCA reduced that dataset to 6 principal components, an 88% reduction in the size of the data.

The six components accounted for 56.62% of the explained variance.

Principal Components 1 and 2 accounted for the largest of the explained variance of 24.84% between the two. Of the original variables in the dataset, Tenure and Bandwidth_GB_Year had the strongest correlation to PC1, while PC 2 had the strongest correlations to Lat and population.

Part V: Attachments

E. Record the web sources used to acquire data or segments of third-party code to support the analysis. Ensure the web sources are reliable.

Centellegher, Simone, PhD – How to compute PCA loadings and the loading matrix with scikit-learn. Data scientist and Researcher. (2020, January 27). Retrieved June 10, 2022, from https://scentellegher.github.io/machine-learning/2020/01/27/pca-loadings-sklearn.html (https://scentellegher.github.io/machine-learning/2020/01/27/pca-loadings-sklearn.html)

F. Acknowledge sources, using in-text citations and references, for content that is quoted, paraphrased, or summarized.

"D212 – Data Mining II" Datacamp, April-Mary 2022, https://app.datacamp.com/learn/custom-tracks/custom-data-mining-ii (https://app.datacamp.com/learn/custom-tracks/custom-data-mining-ii)

Brems, M. (2022, January 26). A one-stop shop for principal component analysis. Medium. Retrieved June 10, 2022, from https://towardsdatascience.com/a-one-stop-shop-for-principal-component-analysis-5582fb7e0a9c (https://towardsdatascience.com/a-one-stop-shop-for-principal-component-analysis-5582fb7e0a9c)

G. Demonstrate professional communication in the content and presentation of your submission.

In [ ]: