Health Insurance Loan prediction

Build machine model to predict whether the person will be interested in health policy or not.The prediction based on the customer demographic details, previous policy details.

Import the necessary packages

In [3]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

Load the dataset

In [4]:
```
train=pd.read_csv('train_Df64byy.csv')
test=pd.read_csv('test_YCcRUnU.csv')
```

Let see basic information about the train and test data

Train data

In [5]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50882 entries, 0 to 50881
Data columns (total 14 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   ID                       50882 non-null  int64  
 1   City_Code                50882 non-null  object 
 2   Region_Code              50882 non-null  int64  
 3   Accomodation_Type        50882 non-null  object 
 4   Reco_Insurance_Type      50882 non-null  object 
 5   Upper_Age                50882 non-null  int64  
 6   Lower_Age                50882 non-null  int64  
 7   Is_Spouse                50882 non-null  object 
 8   Health Indicator         39191 non-null  object 
 9   Holding_Policy_Duration  30631 non-null  object 
 10  Holding_Policy_Type      30631 non-null  float64
 11  Reco_Policy_Cat          50882 non-null  int64  
 12  Reco_Policy_Premium      50882 non-null  float64
 13  Response                 50882 non-null  int64  
dtypes: float64(2), int64(6), object(6)
memory usage: 4.3+ MB
```

Train dataset contains 12 column and 50881 observation.The target column is **Response**

Test data

In [6]:
```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21805 entries, 0 to 21804
Data columns (total 13 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   ID                       21805 non-null  int64  
 1   City_Code                21805 non-null  object 
```

```
 2   Region_Code              21805 non-null  int64
 3   Accomodation_Type        21805 non-null  object
 4   Reco_Insurance_Type      21805 non-null  object
 5   Upper_Age                21805 non-null  int64
 6   Lower_Age                21805 non-null  int64
 7   Is_Spouse                21805 non-null  object
 8   Health Indicator         16778 non-null  object
 9   Holding_Policy_Duration  13202 non-null  object
 10  Holding_Policy_Type      13202 non-null  float64
 11  Reco_Policy_Cat          21805 non-null  int64
 12  Reco_Policy_Premium      21805 non-null  float64
dtypes: float64(2), int64(5), object(6)
memory usage: 1.7+ MB
```

Test dataset contains 12 columns and 21805 observations.

Lets take quick look at a train and test dataset

Train data

In [7]:

```
train.head()
```

Out[7]:

	ID	City_Code	Region_Code	Accomodation_Type	Reco_Insurance_Type	Upper_Age	Lower_Age
0	1	C3	3213	Rented	Individual	36	36
1	2	C5	1117	Owned	Joint	75	22
2	3	C5	3732	Owned	Individual	32	32
3	4	C24	4378	Owned	Joint	52	48
4	5	C8	2190	Rented	Individual	44	44

Test data

In [8]:

```
test.head()
```

Out[8]:

	ID	City_Code	Region_Code	Accomodation_Type	Reco_Insurance_Type	Upper_Age	Lower_Ag
0	50883	C1	156	Owned	Individual	30	3
1	50884	C4	7	Owned	Joint	69	6
2	50885	C1	564	Rented	Individual	28	2
3	50886	C3	1177	Rented	Individual	23	2
4	50887	C1	951	Owned	Individual	75	7

Exploratory Data Analysis

Lets analyze data by various levels analysis,

```
- Univariate Analysis
- Bivariate Analysis
- Multivariate Analysis
```

Target Column(Response)

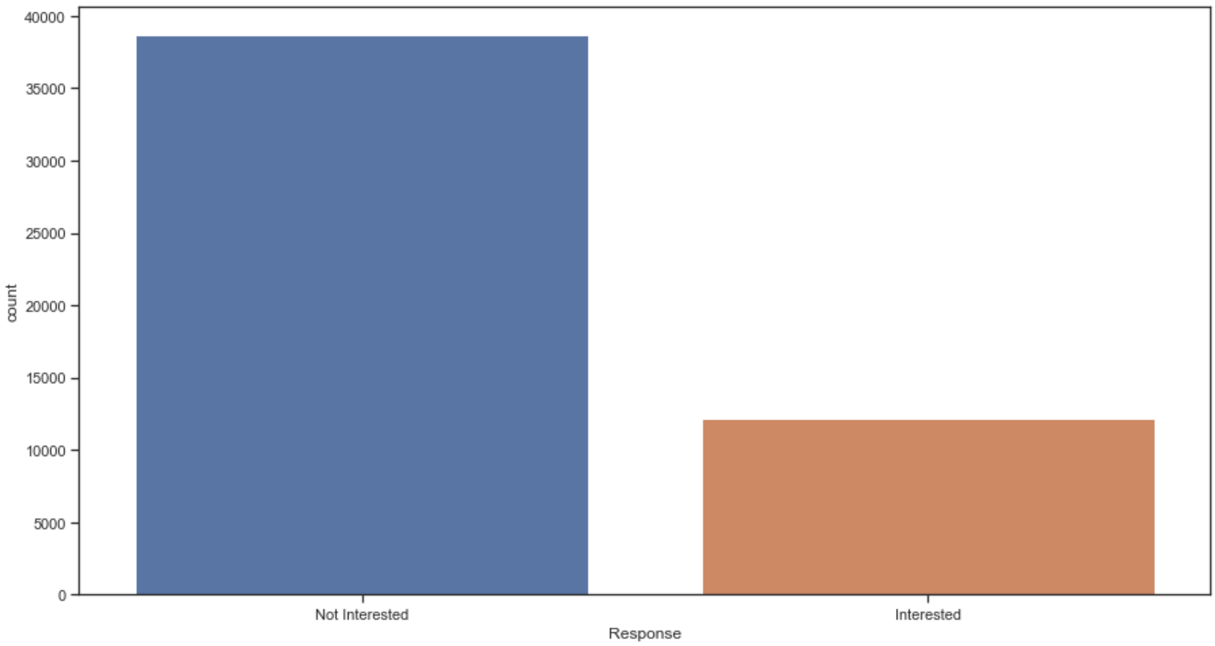
First analyze the target column amd see the type of distribution

Before that the target column is in binary type lets encode it "0" as Not_Interested and "1" as Interested

In [9]:
```
response={0:'Not Interested',1:'Interested'}
```

In [10]:
```
train['Response']=train['Response'].map(response)
```

In [11]:
```
plt.figure(figsize=(15,8))
sns.set_theme(style="ticks")
target_column=sns.countplot(data=train,x='Response')
```



In [12]:
```
train.Response.value_counts()
```

Out[12]:
```
Not Interested    38673
Interested        12209
Name: Response, dtype: int64
```

The above bar chart explains that most of the customers are not interested to take recommended policies.

There is a class imbalance(the customer response biased to one class(not interested in recommended policy))

City Code

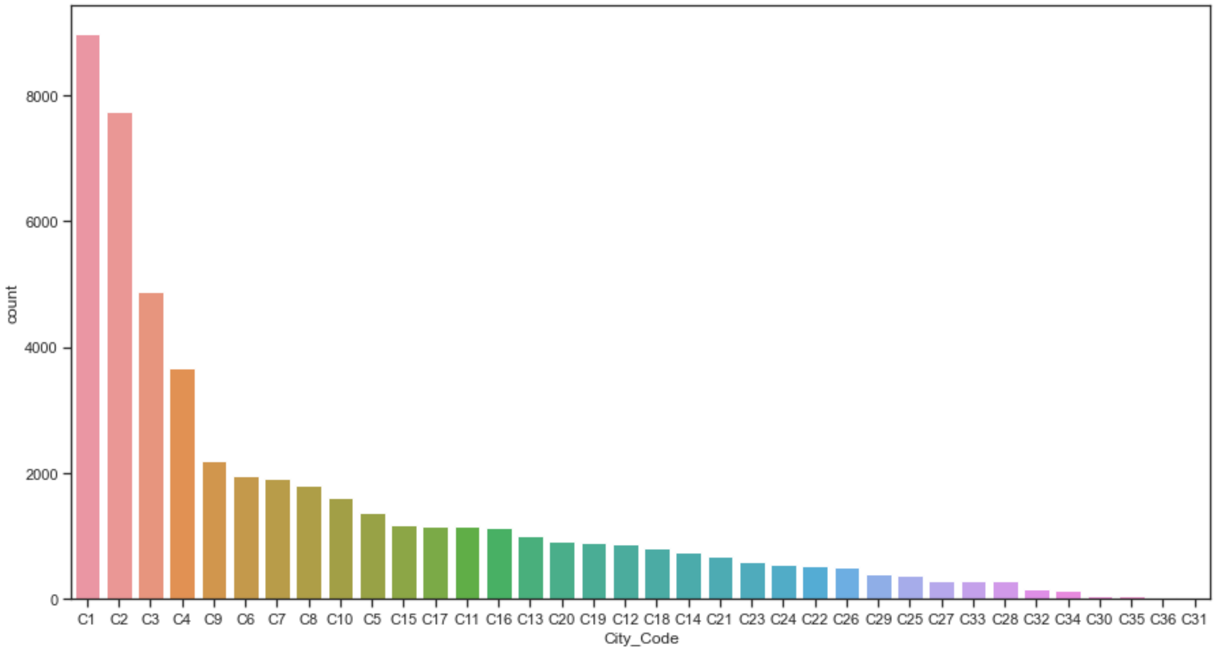
Lets see the number of cities and see how many customers are there.

In [13]:
```
train.City_Code.nunique()
```

Out[13]: 36

In [14]:
```
plt.figure(figsize=(15,8))
```

```
sns.set_theme(style="ticks")
city_code_column=sns.countplot(data=train,x='City_Code',order=train['City_Code'].val
```



There are totally 36 cities.

In that C1, C2, and C3 cities customer have filled more than 4000 health policy form.

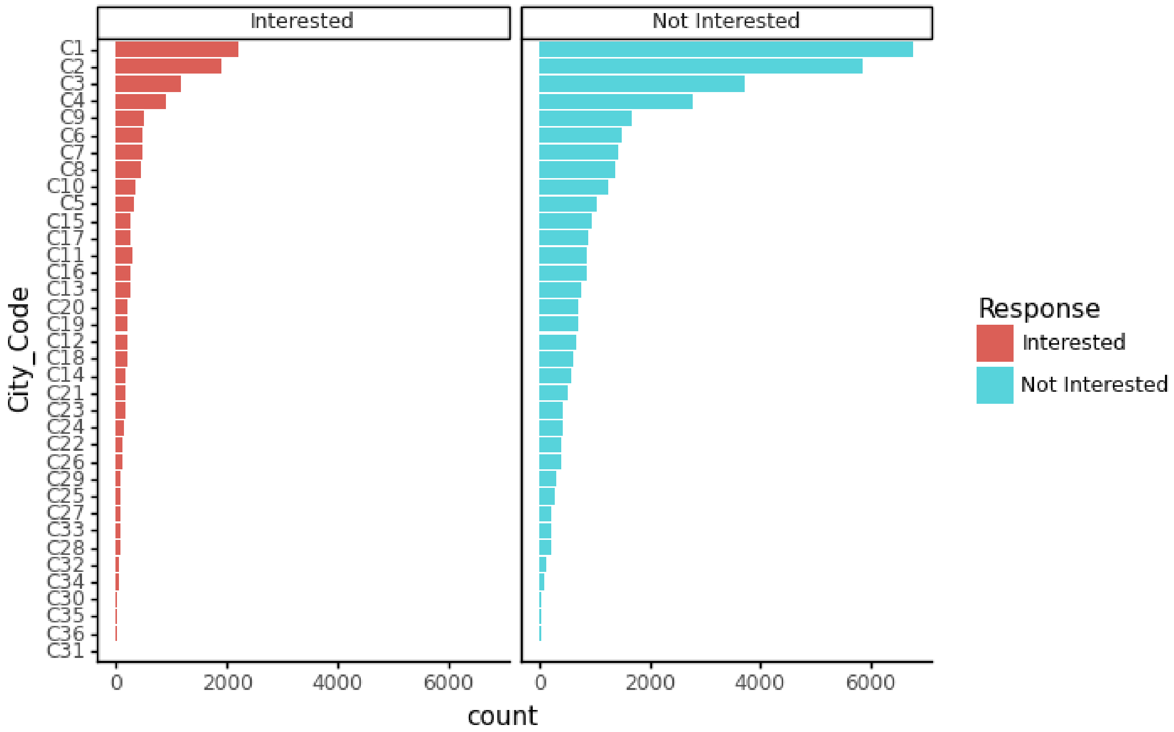
Let's see city-wise customers interests in recommended policy

In [15]:

```
from plotnine import *
```

In [16]:

```
citycode_response=(ggplot(train) +
 geom_bar(aes(x='City_Code', fill='Response'),size=30)+
   scale_x_discrete(limits=train['City_Code'].value_counts().index.tolist()[::-1])+
 facet_wrap('Response')+
 coord_flip()+ theme_classic())
citycode_response
```



Out[16]: <ggplot: (17165698)>

In [17]:

```
train.groupby(['City_Code','Response'],as_index=False)['Response'].agg({'total':'cou
```

Out[17]:

	City_Code	Response	total
1	C1	Not Interested	6765
23	C2	Not Interested	5854
45	C3	Not Interested	3728
61	C4	Not Interested	2782
0	C1	Interested	2208
...	...	...	...
46	C30	Interested	18
56	C35	Interested	16
49	C31	Not Interested	13
58	C36	Interested	5
48	C31	Interested	2

72 rows × 3 columns

The above chart explains that C1 and C2 Customers are highly interested in recommended policies when compare to the other city customers

Region Code

Let's see the number of regions and region-wise customer interests in recommended policy.

In [18]:

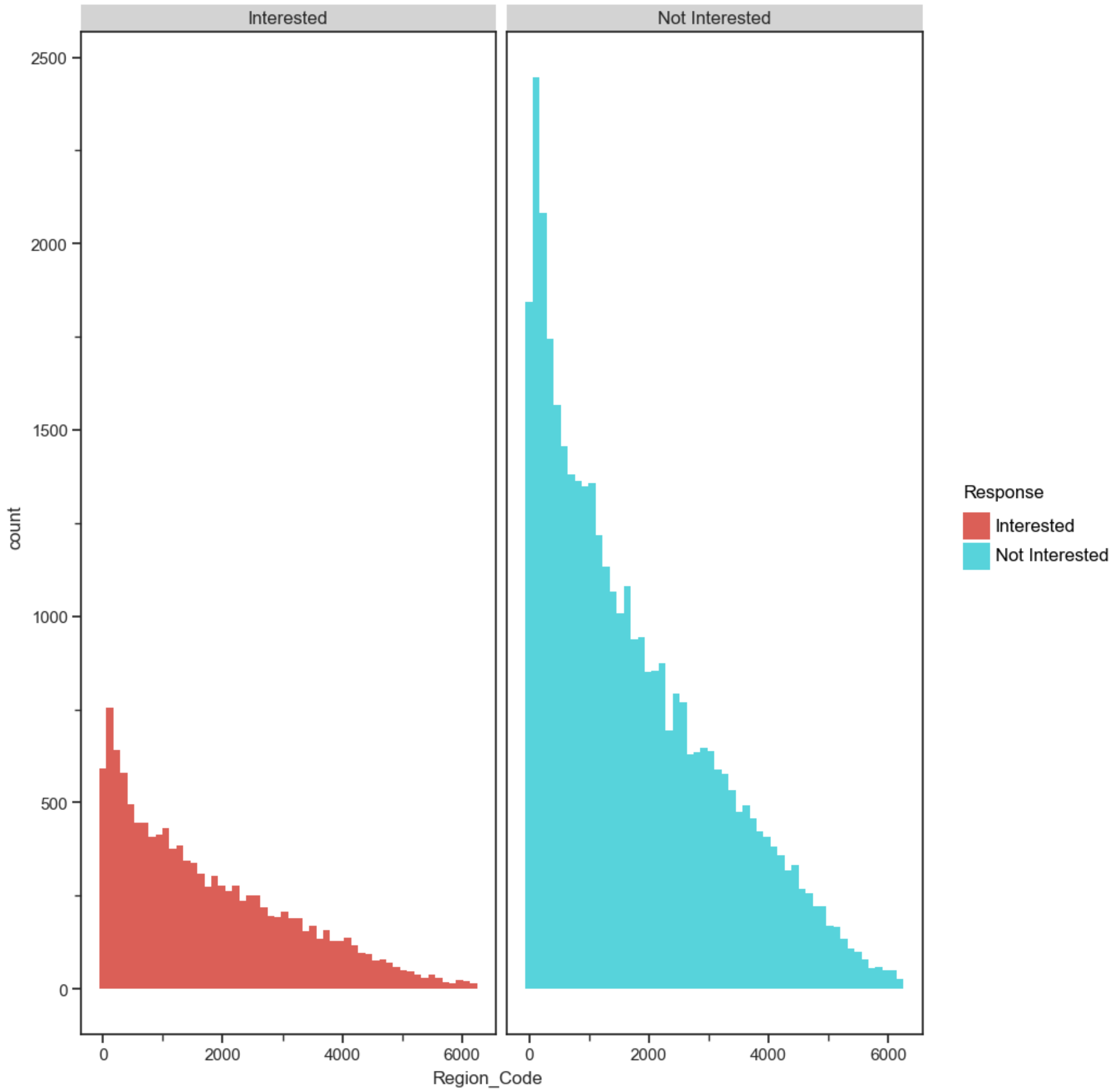
```
train.Region_Code.nunique()
```

Out[18]: 5316

In [19]:

```
regioncode_response=(ggplot(train, aes(x='Region_Code',fill='Response'))+geom_histog
                     facet_wrap('Response')+
theme_seaborn(style="ticks")+
            theme(figure_size=(10,12)) )
regioncode_response
```

```
C:\Users\Balaji\AppData\Local\Programs\Python\Python38-32\lib\site-packages\plotnine
\stats\stat_bin.py:93: PlotnineWarning: 'stat_bin()' using 'bins = 54'. Pick better
value with 'binwidth'.
```



Out[19]: <ggplot: (-2130219570)>

The above chart explains that customer's interest in recommended policy gradually decreasing.

Accomodation Type

Let's see how many customers are living in their own house or rented house and see how their interests vary in recommended policy.

In [20]:

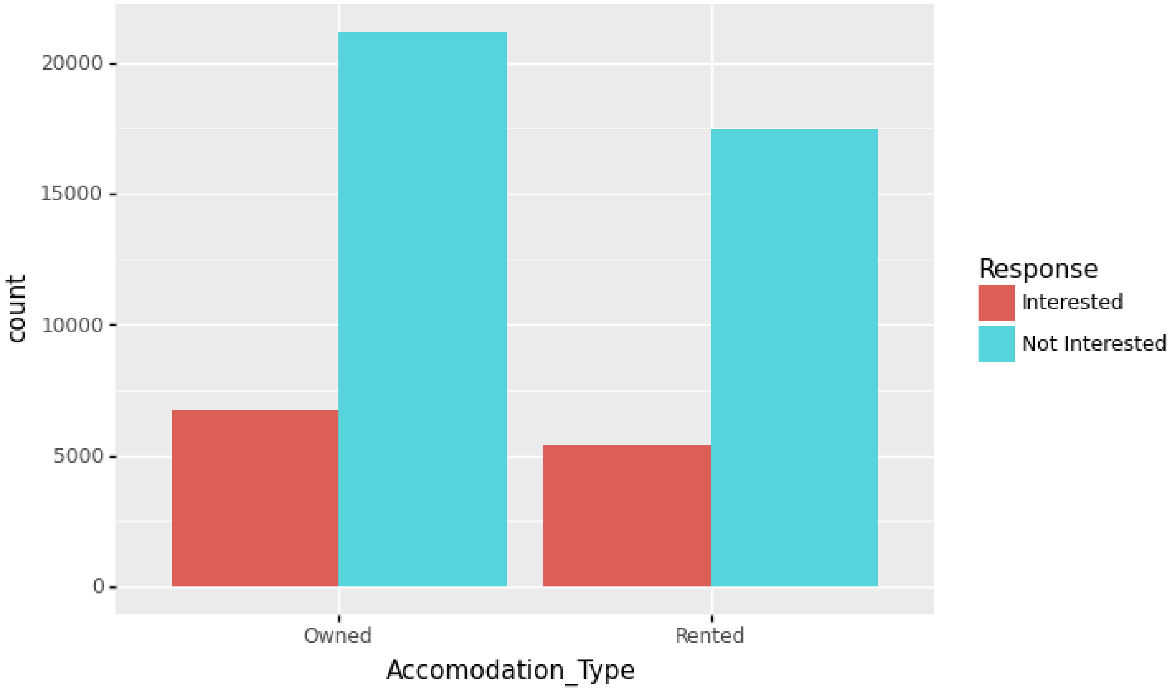
```
train.groupby( ['Accomodation_Type','Response'])['Response'].agg(['count']).reset_in
```

Out[20]:

	Accomodation_Type	Response	count
0	Owned	Interested	6763
1	Owned	Not Interested	21188
2	Rented	Interested	5446
3	Rented	Not Interested	17485

In [21]:

```
(ggplot(train)+geom_bar(aes(x='Accomodation_Type',fill='Response'), position='dodge'
```



Out[21]: <ggplot: (-2130189154)>

The above chart explains that most of the customers are having own house and their interest in recommended policy is also high

Let's see the city-wise accomodation type and customer response

In [22]:

```
(ggplot(train)+geom_bar(aes(x='Accomodation_Type',fill='Response'), position='dodge'
facet_wrap('City_Code')+theme(figure_size=(15,15),
                              axis_text=element_text(style='oblique',size=10,weight='
                              strip_text=element_text(style='oblique',size=10,weight=
```

Out[22]: <ggplot: (17294502)>

The above chart explains that in c1 to c4 cities more number of customers are having own house. In some cities, customers who are living in the rented house are showing high interest in recommended policy than the own house customers.

Reco Insurance Type

Let's see the various recommended insurance types and customer response to them.

In [23]:

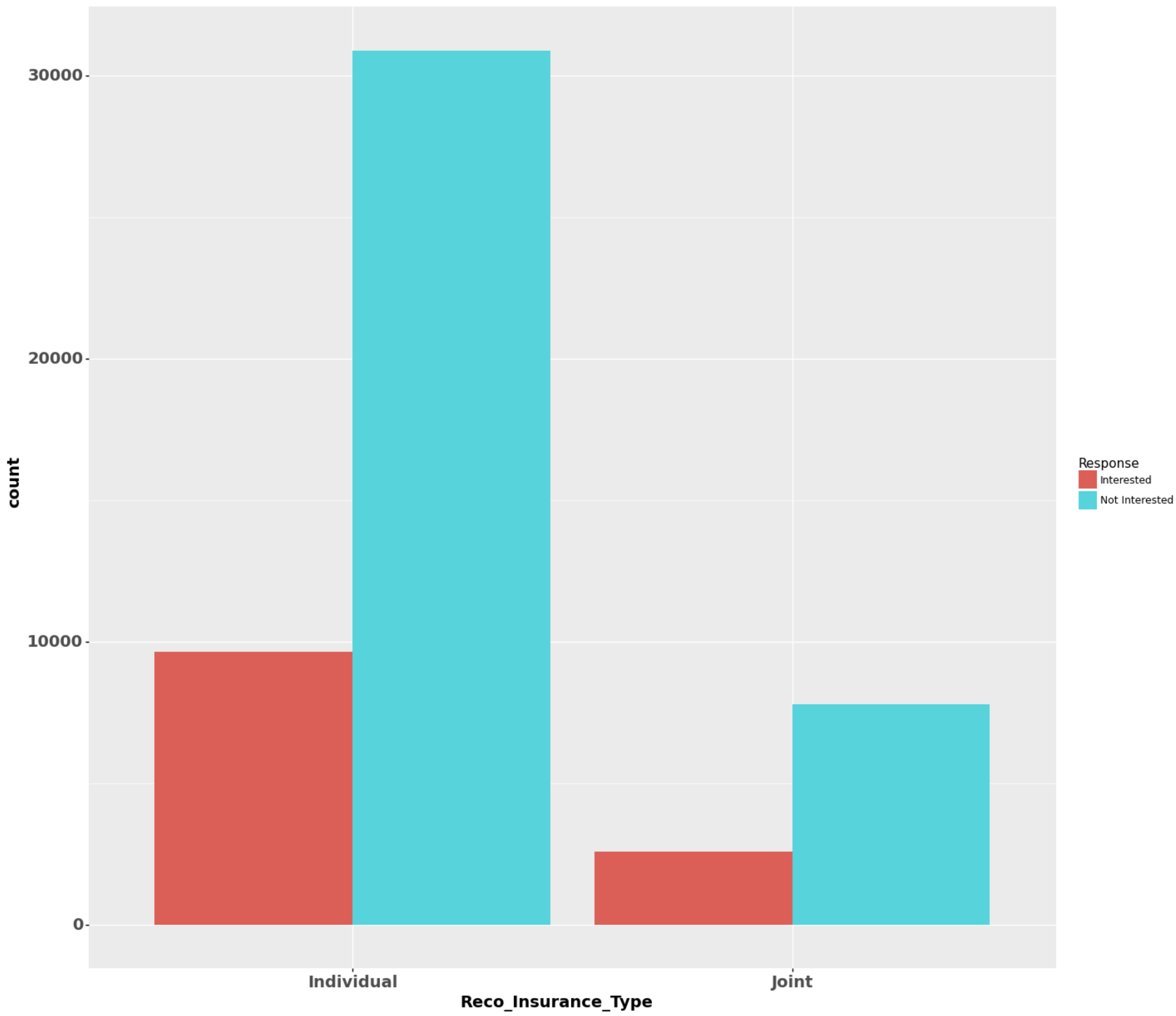
```
train['Reco_Insurance_Type'].value_counts()
```

Out[23]:

```
Individual    40536
Joint         10346
Name: Reco_Insurance_Type, dtype: int64
```

In [24]:

```
(ggplot(train)+geom_bar(aes(x='Reco_Insurance_Type',fill='Response'), position='dodg
theme(figure_size=(15,15),
                             axis_text=element_text(style='normal',size=14,weight='b
                             axis_title=element_text(style='normal',size=14,weight='
                             strip_text=element_text(style='normal',size=14,weight='
```

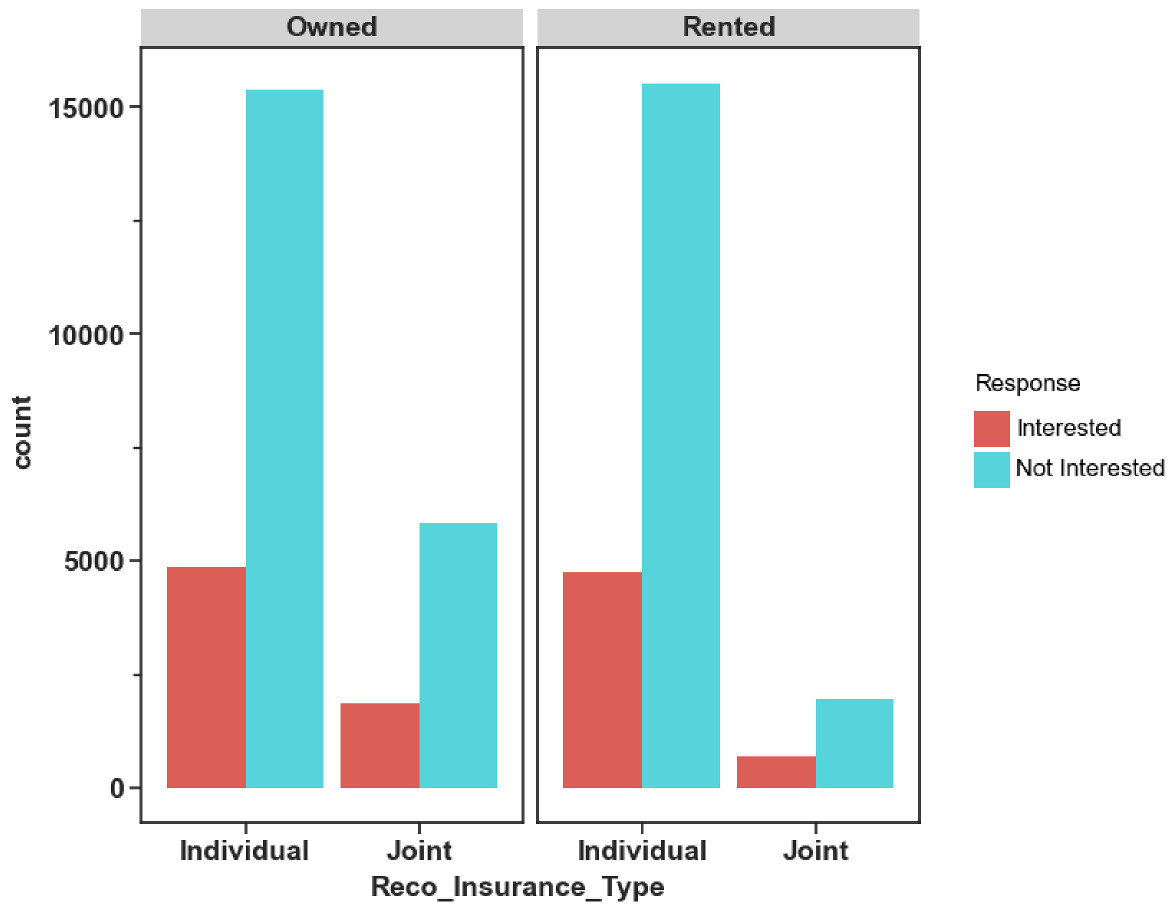


Out[24]: <ggplot: (-2129926898)>

The above chart explains that for more customers, an individual policy is recommended and they are showing high interest to take recommended policy.

Let's see customers accommodation, recommended insurance type and customer responses.

In [25]:
```
(ggplot(train)+geom_bar(aes(x='Reco_Insurance_Type',fill='Response'), position='dodg
 facet_wrap('Accomodation_Type')+
 theme_seaborn(style='ticks')+
theme(figure_size=(7,7),
                             axis_text=element_text(style='normal',size=14,weight='b
                             axis_title=element_text(style='normal',size=14,weight='
                             strip_text=element_text(style='normal',size=14,weight='
```



Out[25]: <ggplot: (17511647)>

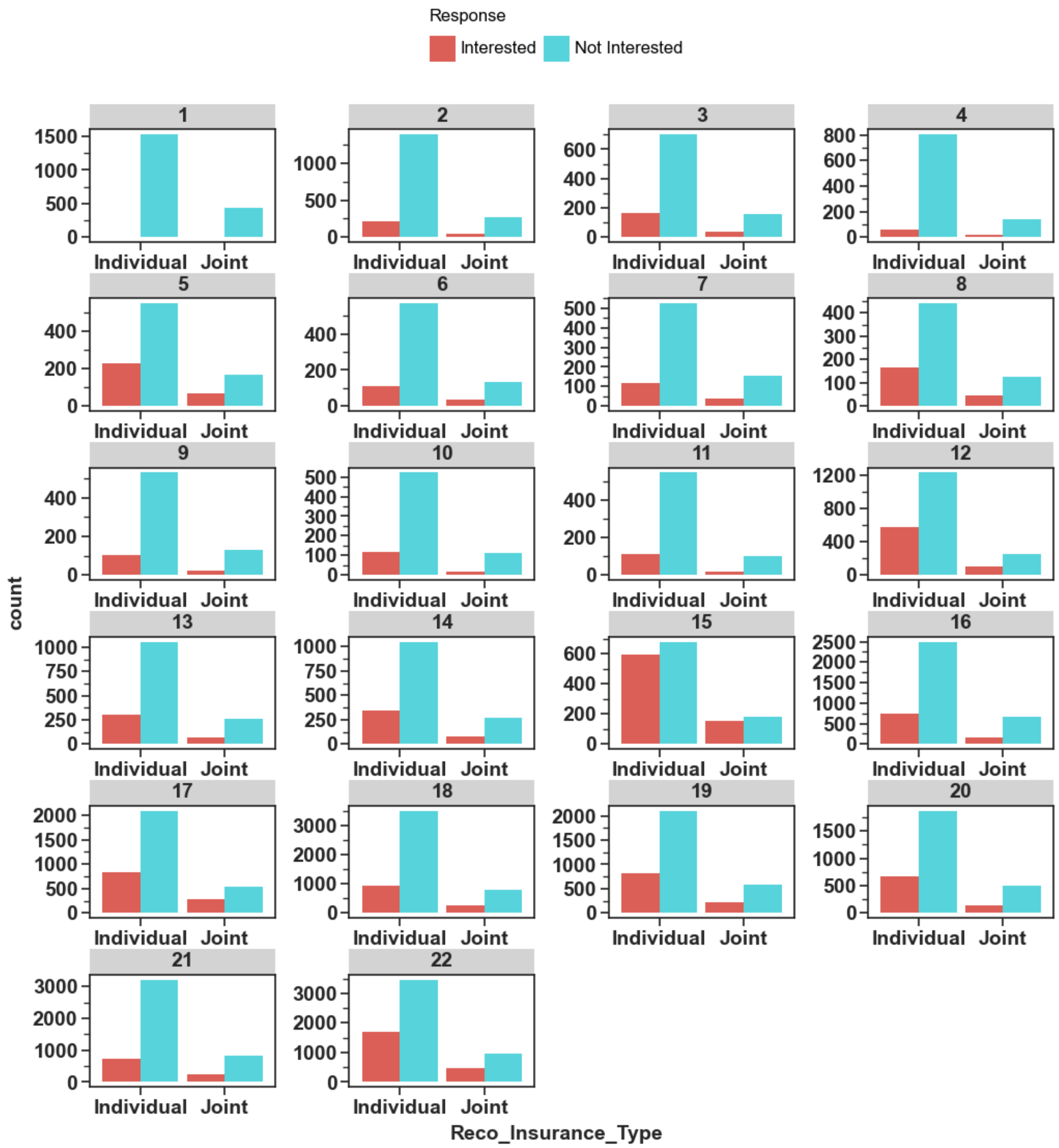
The above chart explains that the customers who are having their own house and living in a rented house are highly recommended to take individual policy. The customers who have recommended take joint policies are less likely to take it.

Recommended Policy Category

Let's see how many categories under the type of recommended policies.

In [26]:

```
(ggplot(train)+geom_bar(aes(x='Reco_Insurance_Type',fill='Response'), position='dodg
facet_wrap('Reco_Policy_Cat',ncol=4,scales="free")+
theme_seaborn(style='ticks')+
theme(figure_size=(12,12),
legend_position='top',
subplots_adjust={'hspace': 0.5,'wspace': 0.4},
axis_text=element_text(style='normal',size=14,weight='bold'),
axis_title=element_text(style='normal',size=14,weight='bold'),
strip_text=element_text(style='normal',size=14,weight='bold')))
```



Out[26]: <ggplot: (17556938)>

The above chart explains that the 12th to 22nd category policies are highly popular in both customers.

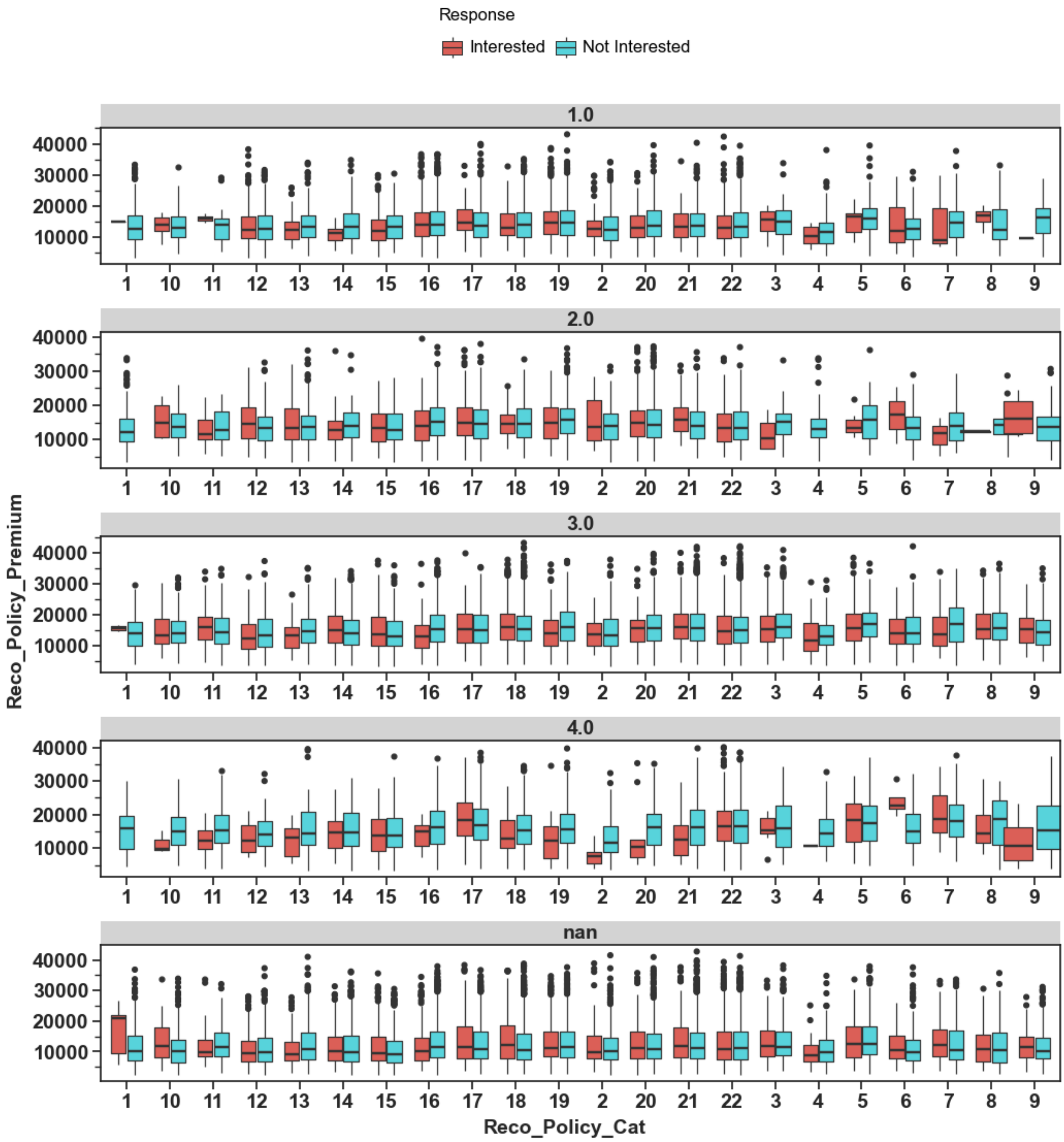
Recommended Policy Premium

Let's see if there is a relationship between the recommended policy premium and recommended policy category.Analyse results with customer's holding policy type and their response to recommended policy.

In [27]:

```
(ggplot(train.astype({'Reco_Policy_Cat':'str'}))+geom_boxplot(aes(x='Reco_Policy_Cat
                                fill='Response'), #position='dodge'
                         )+
facet_wrap('Holding_Policy_Type',nrow=5,scales="free")+
theme_seaborn(style='ticks')+
theme(figure_size=(12,12),
legend_position='top',
subplots_adjust={'hspace': 0.5,'wspace': 0.4},
axis_text=element_text(style='normal',size=14,weight='bold'),
```

```
axis_title=element_text(style='normal',size=14,weight='bold'),
strip_text=element_text(style='normal',size=14,weight='bold')))
```



Out[27]: <ggplot: (-2129616732)>

The above chart explains that there is a difference between the recommended policy type and its premium amount.

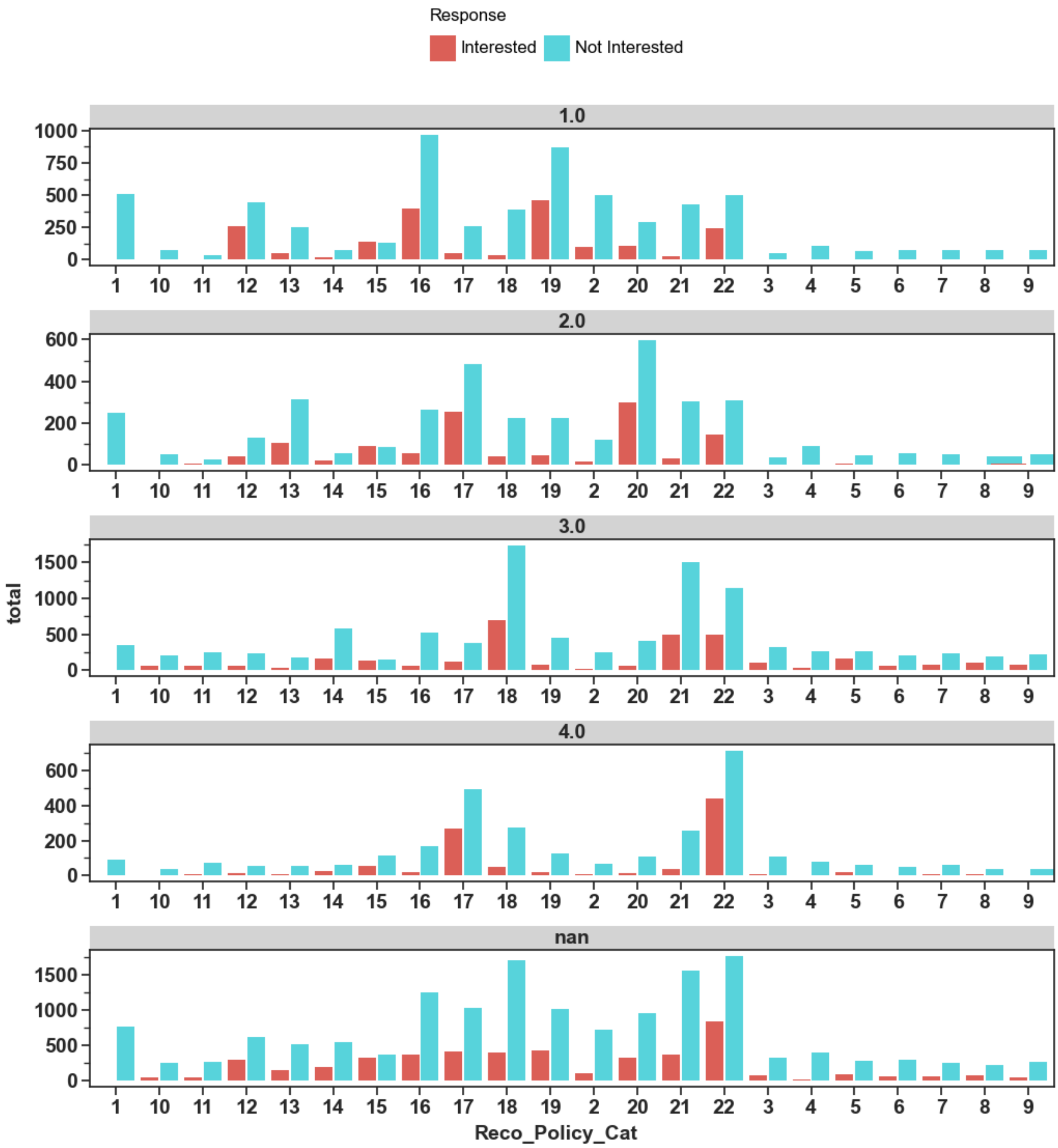
Let's see which type of recommnded policy has more number of customers

In [28]:

```
hold_reco_response=train.groupby(['Holding_Policy_Type','Reco_Policy_Cat','Response'

(ggplot(hold_reco_response.astype({'Reco_Policy_Cat':'str','Holding_Policy_Type':'st
 geom_bar(aes(x='Reco_Policy_Cat',y='total',fill='Response'),stat='identity',positio
facet_wrap('Holding_Policy_Type',nrow=5,scales="free")+
theme_seaborn(style='ticks')+
theme(figure_size=(12,12),
legend_position='top',
subplots_adjust={'hspace': 0.5,'wspace': 0.4},
axis_text=element_text(style='normal',size=14,weight='bold'),
```

```
axis_title=element_text(style='normal',size=14,weight='bold'),
strip_text=element_text(style='normal',size=14,weight='bold')))
```



Out[28]: <ggplot: (-2130034792)>

Let's see city-wise recommended insurance types to customers and their responses to recommended policy.

In [29]:

```
(ggplot(train)+geom_bar(aes(x='Reco_Insurance_Type',fill='Response'), position='dodg
facet_wrap('City_Code',scales='free')+
theme_seaborn(style='ticks')+
theme(figure_size=(15,15),
legend_position='top',
subplots_adjust={'hspace': 0.5,'wspace': 0.4},
axis_text=element_text(style='normal',size=14,weight='bold'),
axis_title=element_text(style='normal',size=14,weight='bold'),
strip_text=element_text(style='normal',size=14,weight='bold')))
```

Out[29]: <ggplot: (-2129928440)>

In [30]:

```
train.groupby(['Reco_Insurance_Type','City_Code','Response']).filter(lambda x: (x['C
```

Out[30]:

	ID	City_Code	Region_Code	Accomodation_Type	Reco_Insurance_Type	Upper_Age	Low
2137	2138	C31	5110	Rented	Individual	59	
13033	13034	C31	5110	Rented	Individual	23	
13367	13368	C31	5617	Owned	Individual	39	
16204	16205	C31	5931	Rented	Individual	32	
18814	18815	C31	5178	Owned	Individual	33	
28210	28211	C31	5569	Rented	Individual	25	

	ID	City_Code	Region_Code	Accomodation_Type	Reco_Insurance_Type	Upper_Age	Low
28835	28836	C31	5079	Rented	Individual	23	
30334	30335	C31	5178	Owned	Individual	26	
34230	34231	C31	5569	Owned	Individual	60	
37561	37562	C31	5344	Rented	Individual	52	
39355	39356	C31	5691	Rented	Individual	34	
42894	42895	C31	5110	Owned	Individual	23	
45119	45120	C31	5079	Rented	Individual	30	
45234	45235	C31	5738	Rented	Individual	28	
45922	45923	C31	5178	Rented	Individual	26	

The above chart explains that in city c31 there is no joint policy recommended to customers.

Upper Age

Let's see the customer's upper age distribution and their responses to the recommended policy.

In [31]:

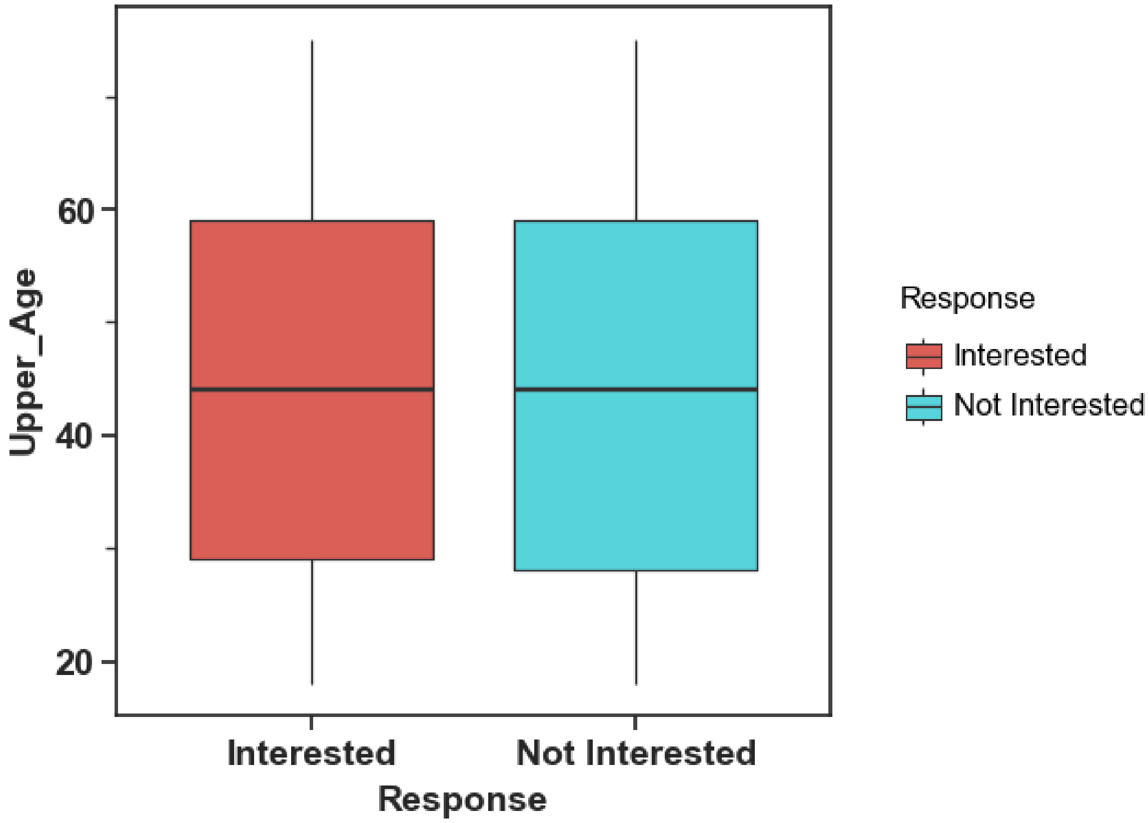
```
train.groupby(['Response']).agg({'Upper_Age':['min','mean','median','max']})
```

Out[31]:

	Upper_Age			
	min	**mean**	**median**	**max**
Response				
Interested	18	44.941682	44	75
Not Interested	18	44.829312	44	75

In [32]:

```
(ggplot(train)+geom_boxplot(aes(x='Response',y='Upper_Age',fill='Response'))+
theme_seaborn(style='ticks')+
theme(figure_size=(5,5),
                             axis_text=element_text(style='normal',size=14,weight='b
                             axis_title=element_text(style='normal',size=14,weight='
                             strip_text=element_text(style='normal',size=14,weight='
```



Out[32]: <ggplot: (-2129715018)>

The above boxplot explains that there is no significant difference between the age of customer who is interested or not interested in recommended policies.

Let's analyze the customer's upper age with their type of accommodation and recommended policy types to them and also their interest in the recommended policy.

In [33]:

```
train.groupby(['Accomodation_Type','Reco_Insurance_Type','Response']).agg({'Upper_Ag
```

Out[33]:

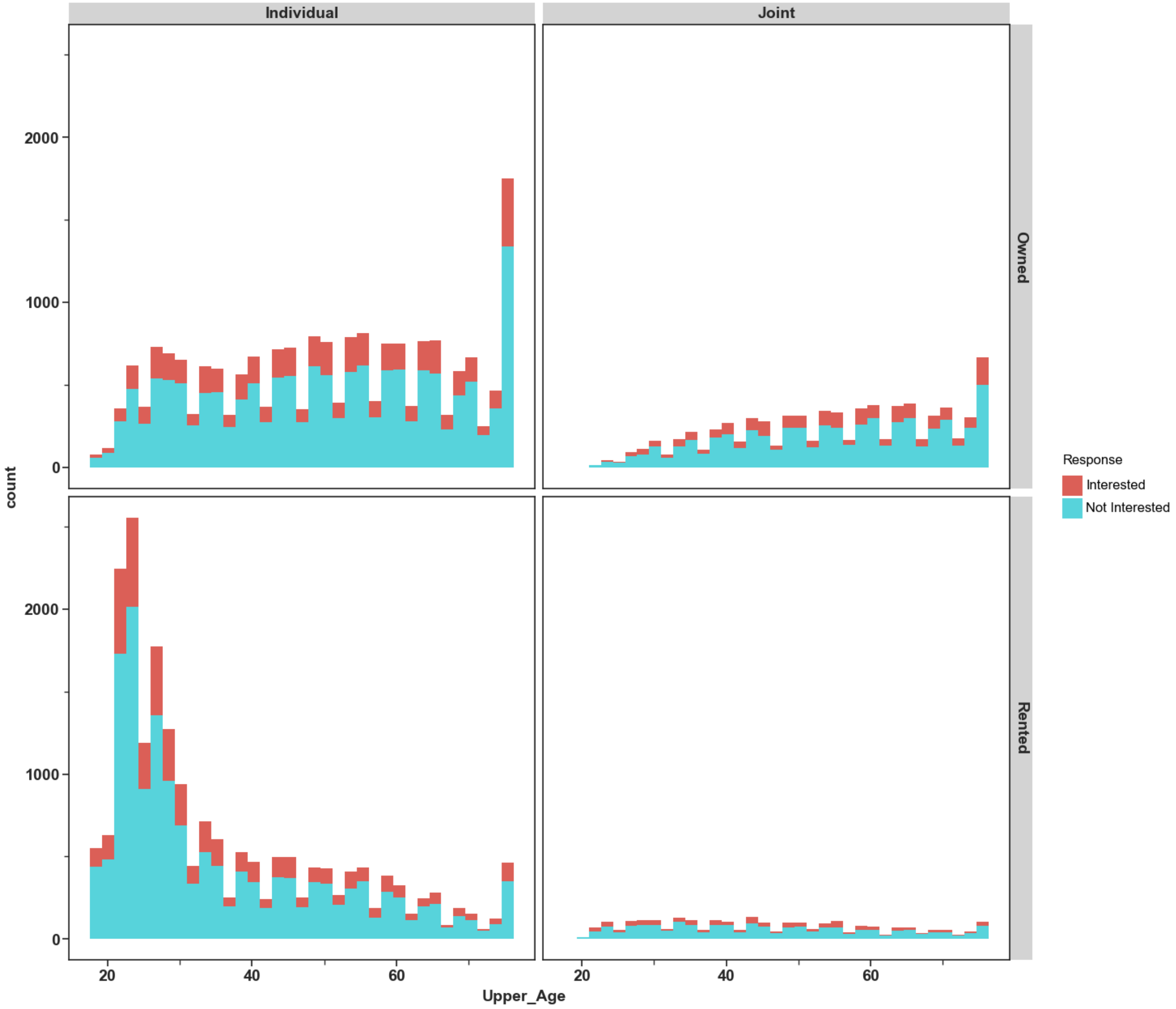
			Upper_Age			
			min	median	mean	max
Accomodation_Type	Reco_Insurance_Type	Response				
Owned	Individual	Interested	18	51	49.849980	75
		Not Interested	18	51	50.105034	75
	Joint	Interested	20	56	54.786361	75
		Not Interested	19	57	55.168617	75
Rented	Individual	Interested	18	30	35.923854	75
		Not Interested	18	29	35.632603	75
	Joint	Interested	21	44	45.534682	75
		Not Interested	19	44	45.603562	75

In [34]:

```
(ggplot(train)+geom_histogram(aes(x='Upper_Age',fill='Response'))+
facet_grid('Accomodation_Type~Reco_Insurance_Type')+
theme_seaborn(style='ticks')+
theme(figure_size=(15,15),
```

```
                                        axis_text=element_text(style='normal',size=14,weight='b
                                        axis_title=element_text(style='normal',size=14,weight='
                                        strip_text=element_text(style='normal',size=14,weight='
```

```
C:\Users\Balaji\AppData\Local\Programs\Python\Python38-32\lib\site-packages\plotnine
\stats\stat_bin.py:93: PlotnineWarning: 'stat_bin()' using 'bins = 35'. Pick better
value with 'binwidth'.
```



Out[34]: <ggplot: (-2129000895)>

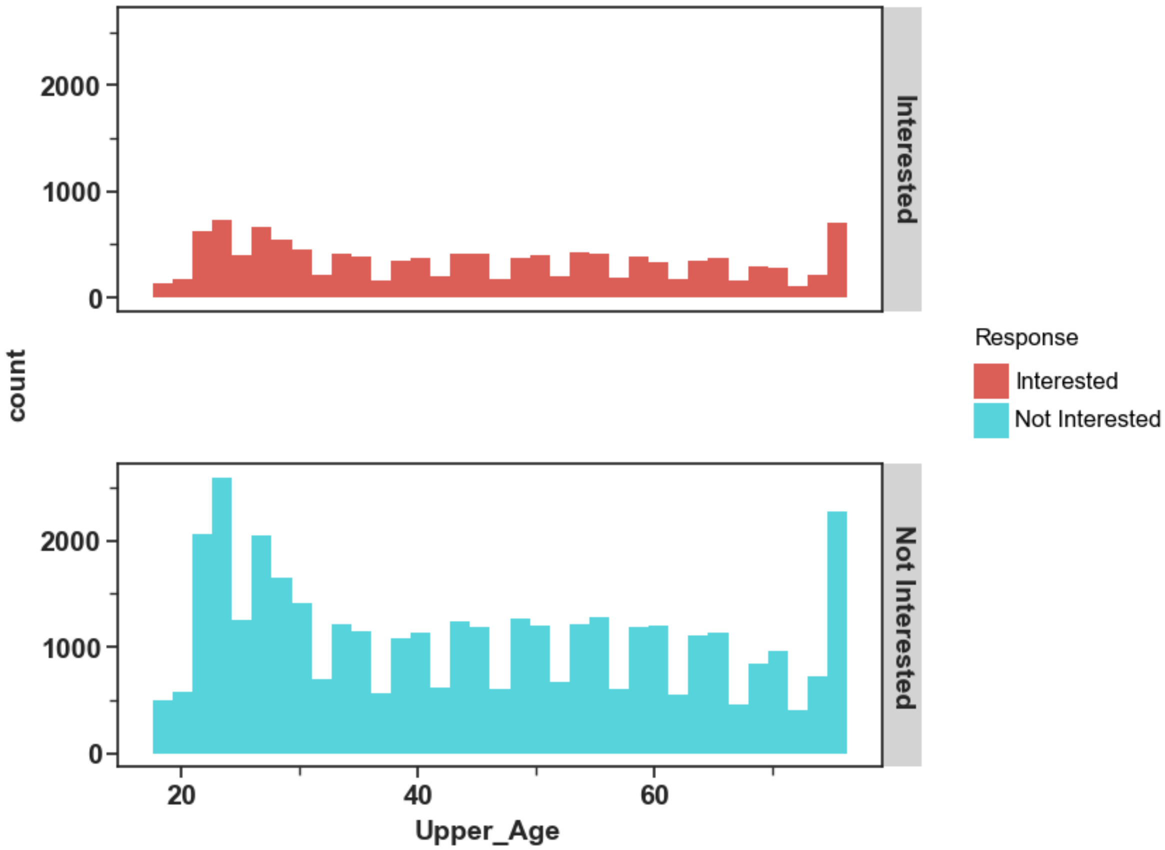
The above chart explains that rented house customers in the age range of 20 to 30 years are highly interested to take recommended policy. Moreover, own house customers whose age is 70 and above showing high interest in the recommended policy than to middle age customers.

In [ ]:

In [35]:

```
(ggplot(train)+geom_histogram(aes(x='Upper_Age',fill='Response'))+
facet_grid('Response~')+
theme_seaborn(style='ticks')+
theme(figure_size=(7,7),    subplots_adjust={'hspace': 0.5,'wspace': 0.4},
                                axis_text=element_text(style='normal',size=14,weight=
                              axis_title=element_text(style='normal',size=14,weight='
                              strip_text=element_text(style='normal',size=14,weight='
```

```
C:\Users\Balaji\AppData\Local\Programs\Python\Python38-32\lib\site-packages\plotnine
\stats\stat_bin.py:93: PlotnineWarning: 'stat_bin()' using 'bins = 35'. Pick better
value with 'binwidth'.
```



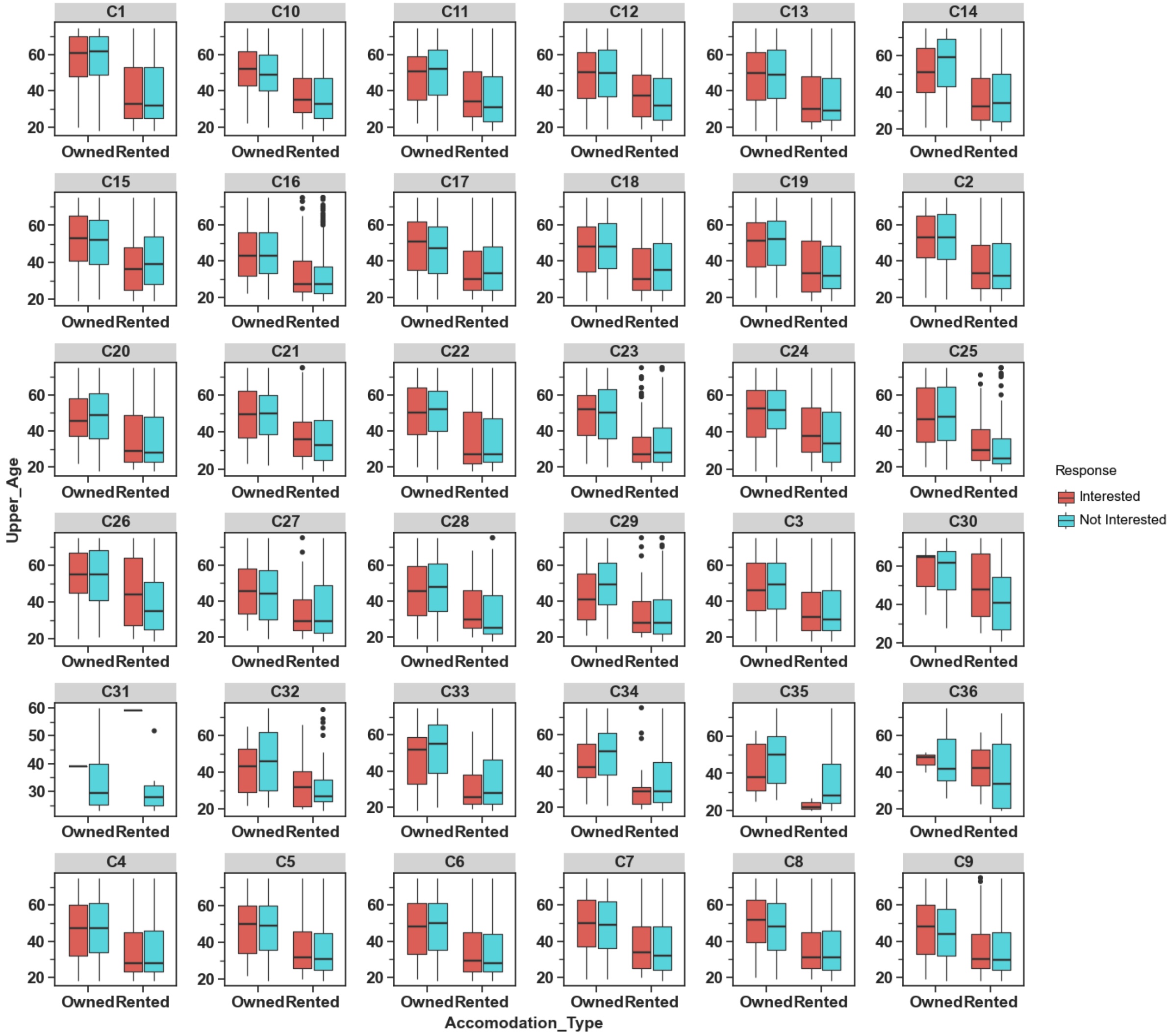
Out[35]: <ggplot: (-2134652686)>

The above chart explains that more number customers are in the age range of 19 to 20

Let's see city-wise customer's upper age distribution and their responses in the recommended policy.

In [36]:

```
(ggplot(train)+geom_boxplot(aes(y='Upper_Age',x='Accomodation_Type',fill='Response')
facet_wrap('City_Code',scales='free')+
theme_seaborn(style='ticks')+
theme(figure_size=(15,15),    subplots_adjust={'hspace': 0.5,'wspace': 0.4},
                               axis_text=element_text(style='normal',size=14,weight=
                              axis_title=element_text(style='normal',size=14,weight='
                              strip_text=element_text(style='normal',size=14,weight='
```



Out[36]: <ggplot: (17295394)>

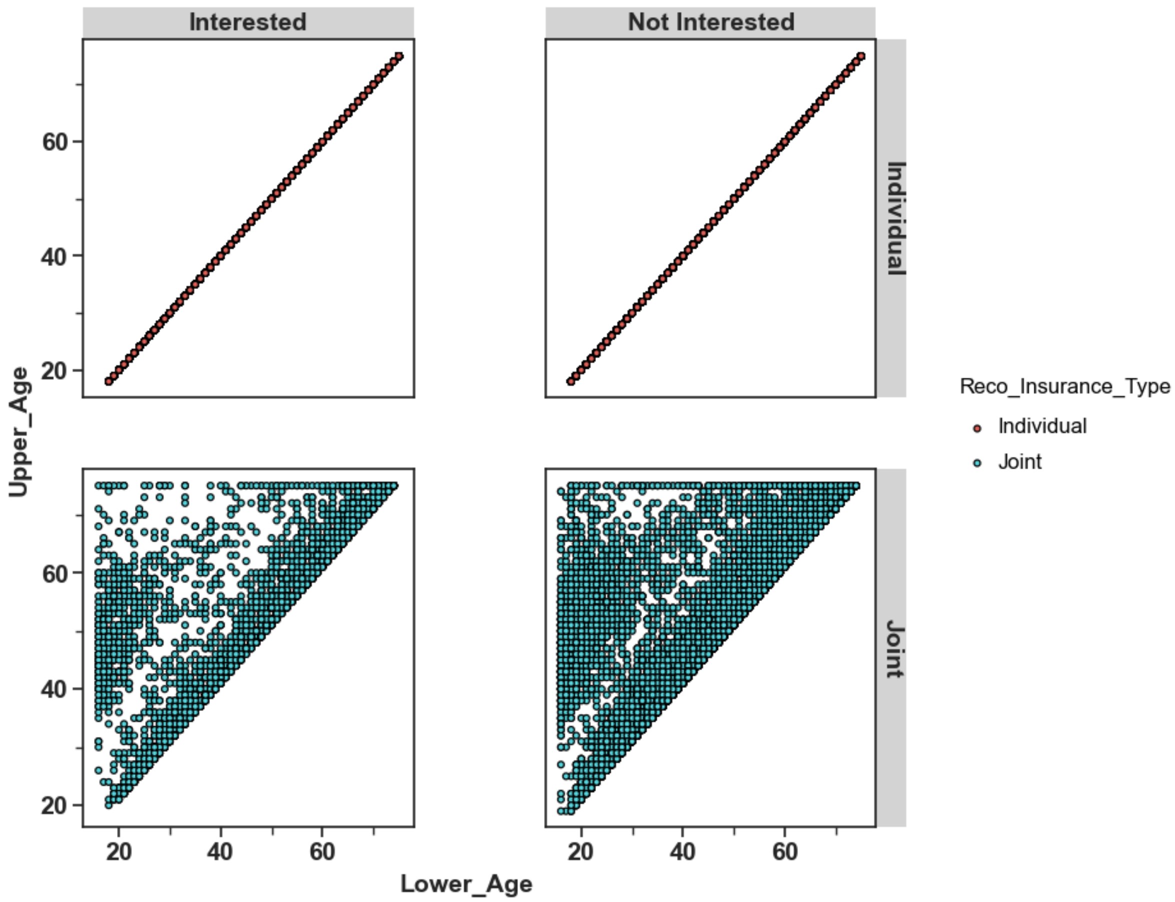
The above chart shows that each city customer's accommodation type has a different age distribution.

Lower Age

If the customer has taken a joint policy that time two members age should have to be recorded. The same thing applies here if the customer has taken an individual policy there is no need to maintain both the upper and lower ages of a customer. If it is a joint policy has to be maintained.

In [37]:

```
(ggplot(train)+geom_point(aes(x='Lower_Age',y='Upper_Age',fill='Reco_Insurance_Type'
facet_grid('Reco_Insurance_Type~Response' ,scales='free')+
theme_seaborn(style='ticks')+
theme(figure_size=(8,8),    subplots_adjust={'hspace': 0.2,'wspace': 0.4},
                              axis_text=element_text(style='normal',size=14,weight=
                            axis_title=element_text(style='normal',size=14,weight='
                            strip_text=element_text(style='normal',size=14,weight='
```



Out[37]: <ggplot: (-2129971979)>

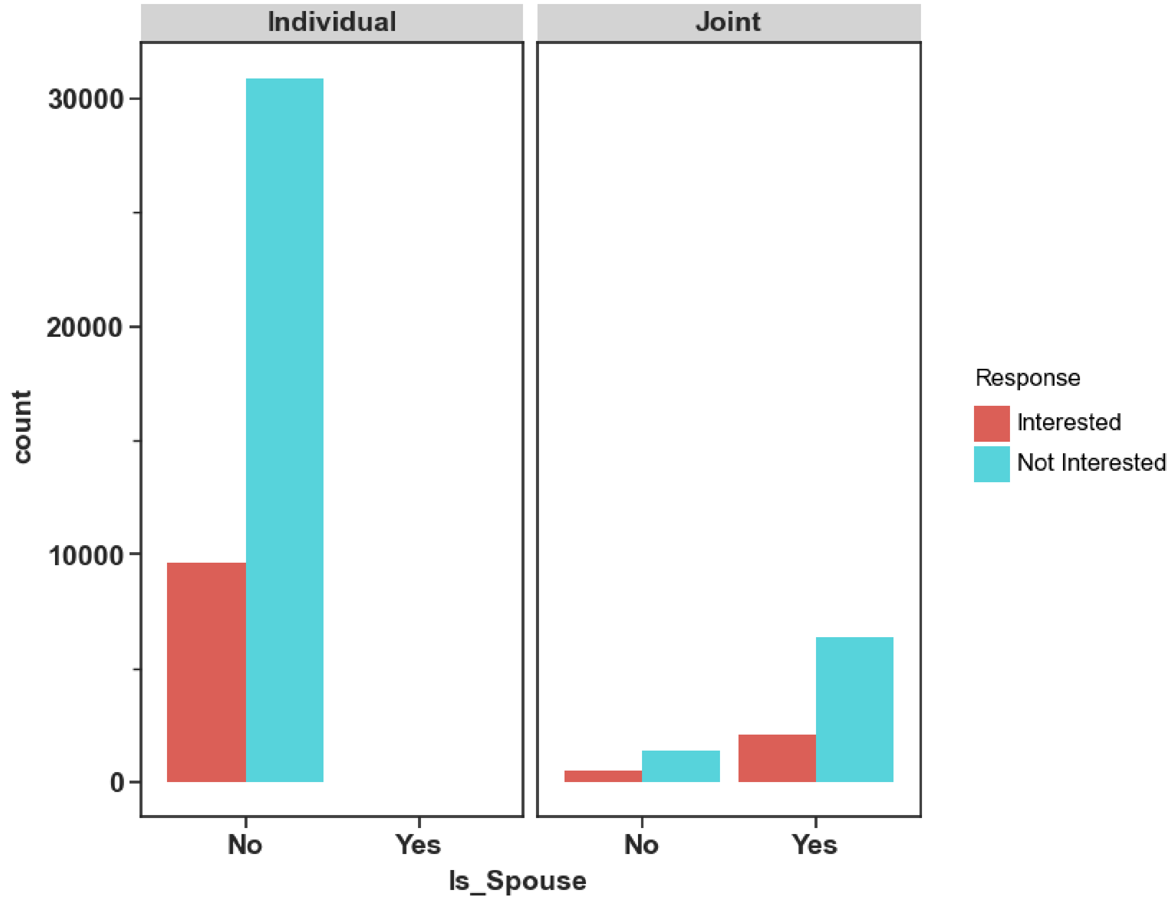
Is Spouse

If the customers are married to each other. Then they are recommended to take a joint policy.

Let's see how many customers are recommended to take a joint policy with their spouse and see is there any difference in their responses to the recommended policy.

In [38]:

```
(ggplot(train)+geom_bar(aes(x='Is_Spouse',fill='Response'), position='dodge')+
 facet_wrap('Reco_Insurance_Type')+
 theme_seaborn(style='ticks')+
theme(figure_size=(7,7),
                             axis_text=element_text(style='normal',size=14,weight='b
                             axis_title=element_text(style='normal',size=14,weight='
                             strip_text=element_text(style='normal',size=14,weight='
```



Out[38]: <ggplot: (17171673)>

In [39]:

```
train.groupby(['Reco_Insurance_Type','Is_Spouse','Response'],as_index=False)['Respon
```

Out[39]:

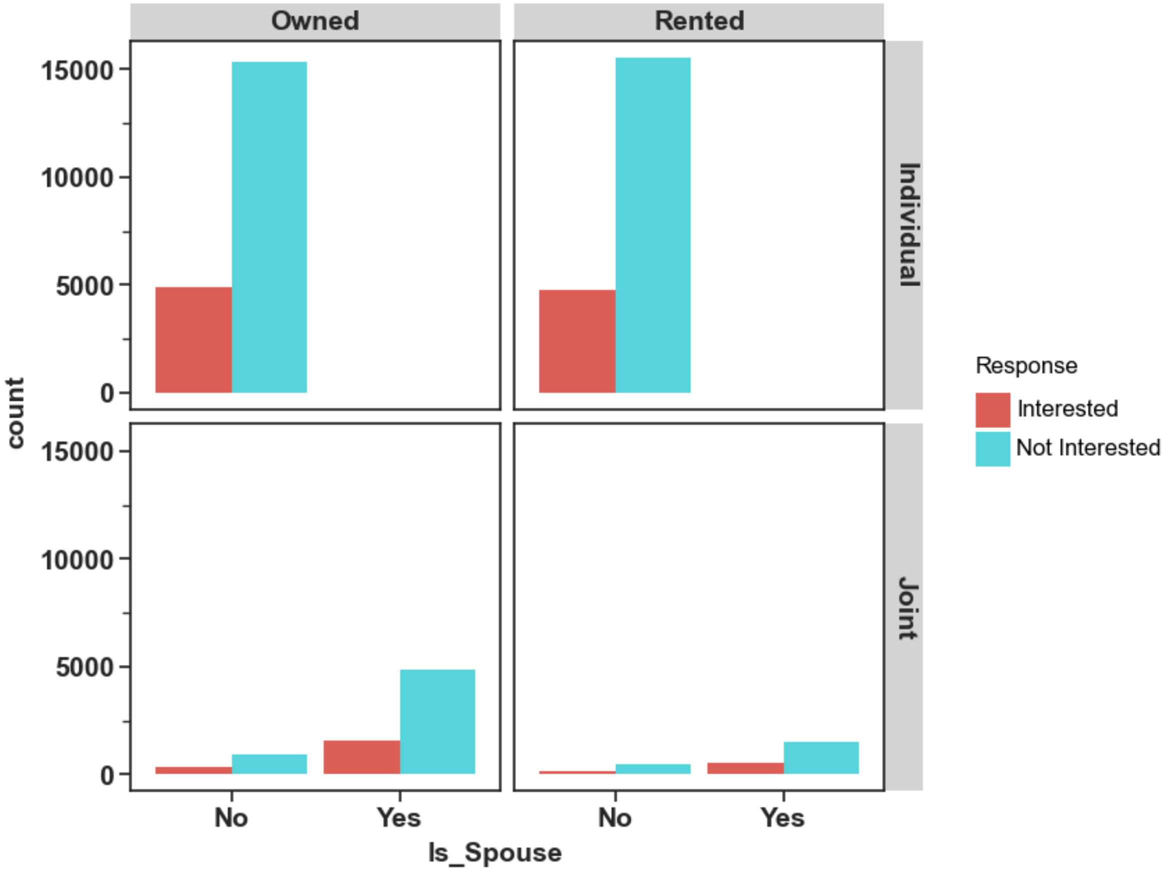
	Reco_Insurance_Type	Is_Spouse	Response	Total
1	Individual	No	Not Interested	30896
0	Individual	No	Interested	9640
5	Joint	Yes	Not Interested	6370
4	Joint	Yes	Interested	2052
3	Joint	No	Not Interested	1407
2	Joint	No	Interested	517

The above chart explains that some customers who are recommended to take the joint policy with their spouse are less interested in that recommended policy.

Let's see how many customers are recommended to take a joint policy with their spouse or other customers. In that how many of them living in own or rented house. Let's see their responses to the recommended policy.

In [40]:

```
(ggplot(train)+geom_bar(aes(x='Is_Spouse',fill='Response'), position='dodge')+
 facet_grid('Reco_Insurance_Type~Accomodation_Type')+
 theme_seaborn(style='ticks')+
theme(figure_size=(7,7),
                             axis_text=element_text(style='normal',size=14,weight='b
                             axis_title=element_text(style='normal',size=14,weight='
                             strip_text=element_text(style='normal',size=14,weight='
```



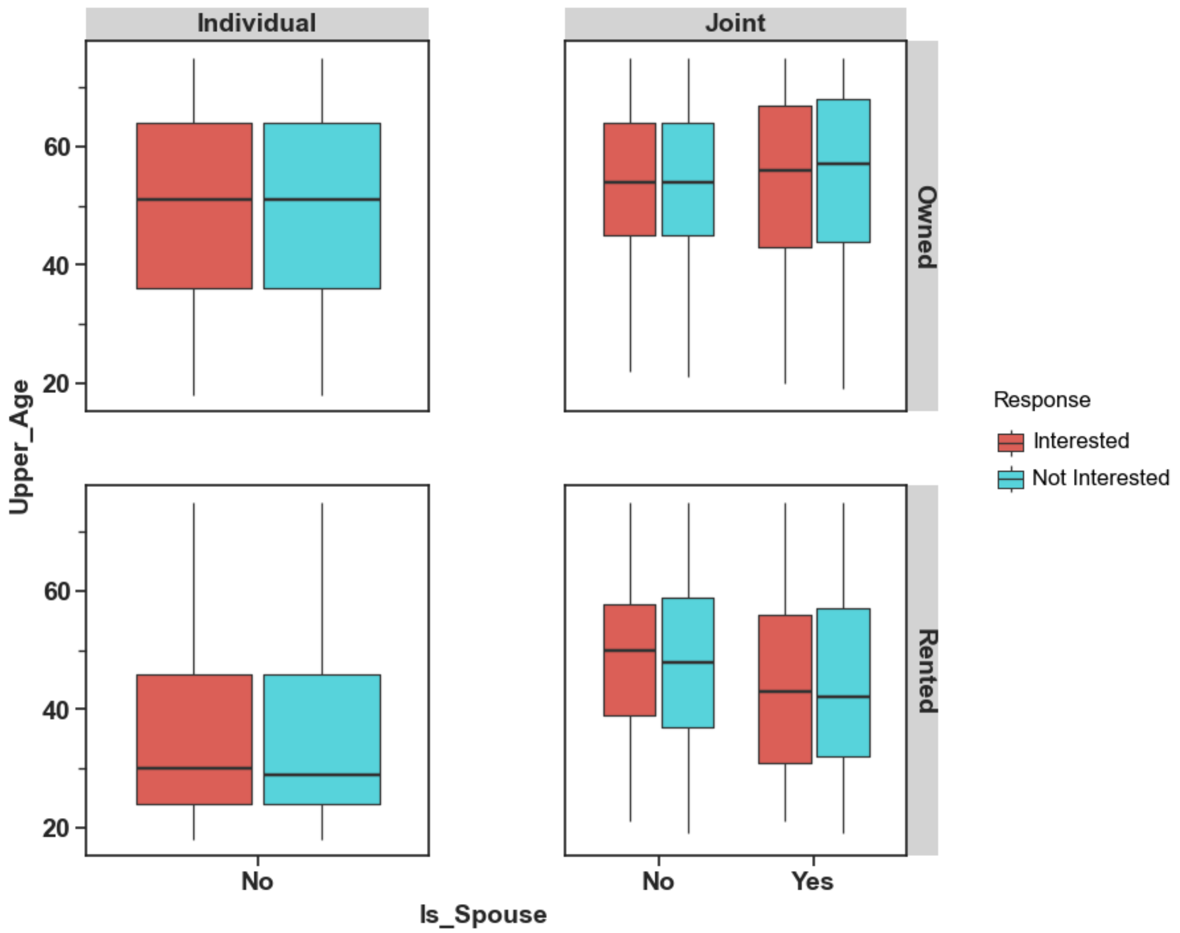
Out[40]: <ggplot: (-2129628547)>

The above chart explains that most of the rented house customers are less interested in a recommended joint policy.

Let's analyze the customer's upper age with their accommodation and their recommended joint policy (that is whether they have taken a recommended joint policy with their spouse or other family members?)

In [41]:

```
(ggplot(train)+geom_boxplot(aes(x='Is_Spouse',y='Upper_Age',fill='Response'))+
facet_grid('Accomodation_Type~Reco_Insurance_Type' ,scales='free')+
theme_seaborn(style='ticks')+
theme(figure_size=(8,8),    subplots_adjust={'hspace': 0.2,'wspace': 0.4},
                               axis_text=element_text(style='normal',size=14,weight=
                             axis_title=element_text(style='normal',size=14,weight='
                             strip_text=element_text(style='normal',size=14,weight='
```



Out[41]: <ggplot: (4073659)>

In [42]:
```
train.groupby(['Is_Spouse','Reco_Insurance_Type','Accomodation_Type','Response']).ag
```

Out[42]:

				Upper_Age			
				min	**median**	**mean**	**max**
Is_Spouse	**Reco_Insurance_Type**	**Accomodation_Type**	**Response**				
No	**Individual**	**Owned**	**Interested**	18	51	49.849980	75
			Not Interested	18	51	50.105034	75
		Rented	**Interested**	18	30	35.923854	75
			Not Interested	18	29	35.632603	75
	Joint	**Owned**	**Interested**	22	54	54.352239	75
			Not Interested	21	54	54.231183	75
		Rented	**Interested**	21	50	48.752747	75
			Not Interested	19	48	47.939203	75
Yes	**Joint**	**Owned**	**Interested**	20	56	54.880674	75
			Not Interested	19	57	55.347194	75
		Rented	**Interested**	21	43	44.386275	75

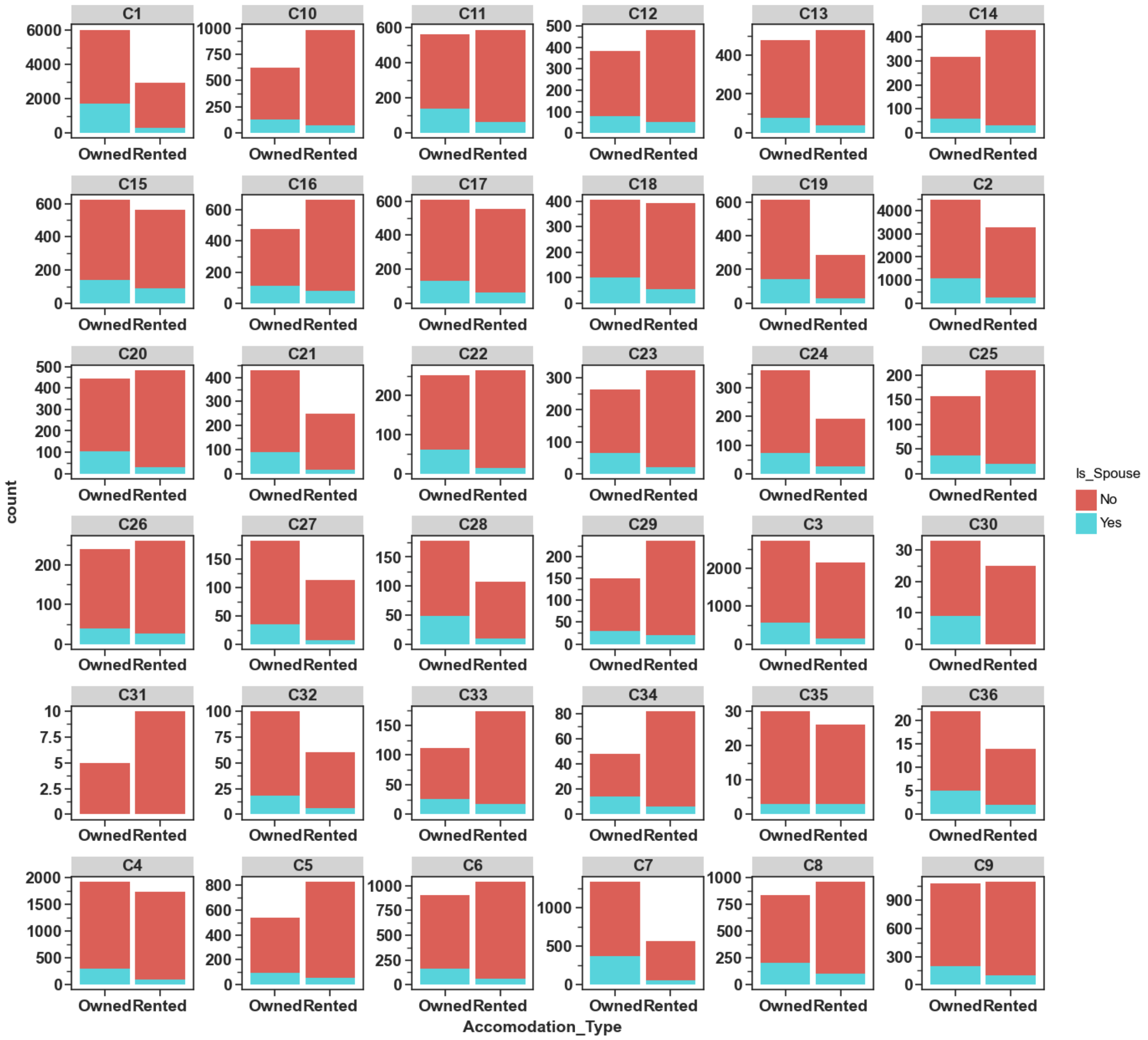
				Upper_Age			
				min	median	mean	max
Is_Spouse	Reco_Insurance_Type	Accomodation_Type	Response				
			Not Interested	19	42	44.854839	75

The above chart explains that the customers who are married and recommended to take the joint policy and the customer who has taken the recommended joint policy with others and their age have a significant difference. The accommodation also plays a major role.

Let's see city-wise the customers who have recommended to take the joint policy with their spouse or with other customers. Check these results with the customer's type of accommodation.

In [43]:

```
(ggplot(train)+geom_bar(aes(x='Accomodation_Type',fill='Is_Spouse'))+
facet_wrap('City_Code',scales='free')+
theme_seaborn(style='ticks')+
theme(figure_size=(15,15),    subplots_adjust={'hspace': 0.5,'wspace': 0.4},
                               axis_text=element_text(style='normal',size=14,weight=
                              axis_title=element_text(style='normal',size=14,weight='
                              strip_text=element_text(style='normal',size=14,weight='
```



Out[43]: <ggplot: (4073527)>

The above chart explains that in city 31 the customers who are having own house and living in a rented house are recommended to take the joint policy with their family members or business partners. Also, the customers who are living in the rented house of City 30 recommend the same.

Health Indicator

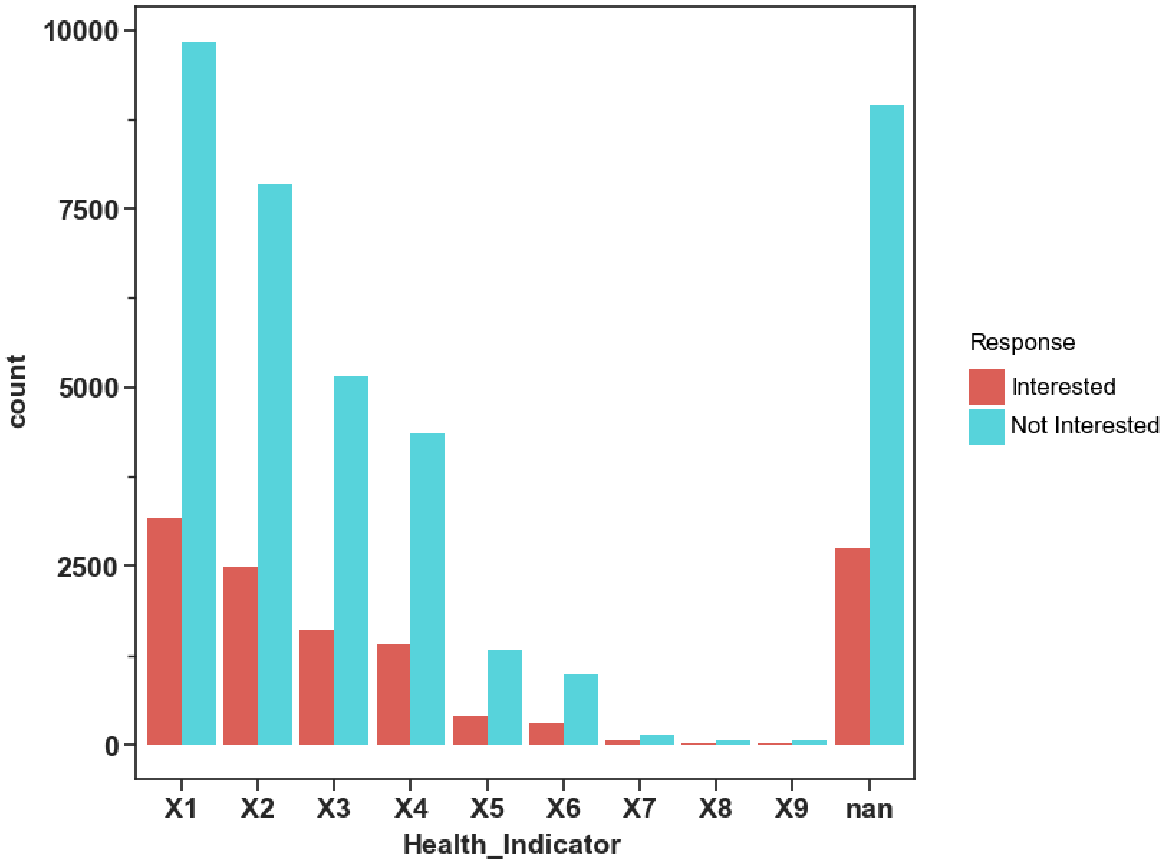
Let's see the customer's health condition types and their responses to the new health policy.

In [44]:

```
train.rename(columns={'Health Indicator':'Health_Indicator'}, inplace=True)
```

In [45]:

```
(ggplot(train)+geom_bar(aes(x='Health_Indicator',fill='Response'), position='dodge')
 theme_seaborn(style='ticks')+
theme(figure_size=(7,7),
                             axis_text=element_text(style='normal',size=14,weight='b
                             axis_title=element_text(style='normal',size=14,weight='
                             strip_text=element_text(style='normal',size=14,weight='
```



Out[45]: <ggplot: (-2130150573)>

In [46]:

```
train['Health_Indicator'].isnull().sum()
```

Out[46]: 11691

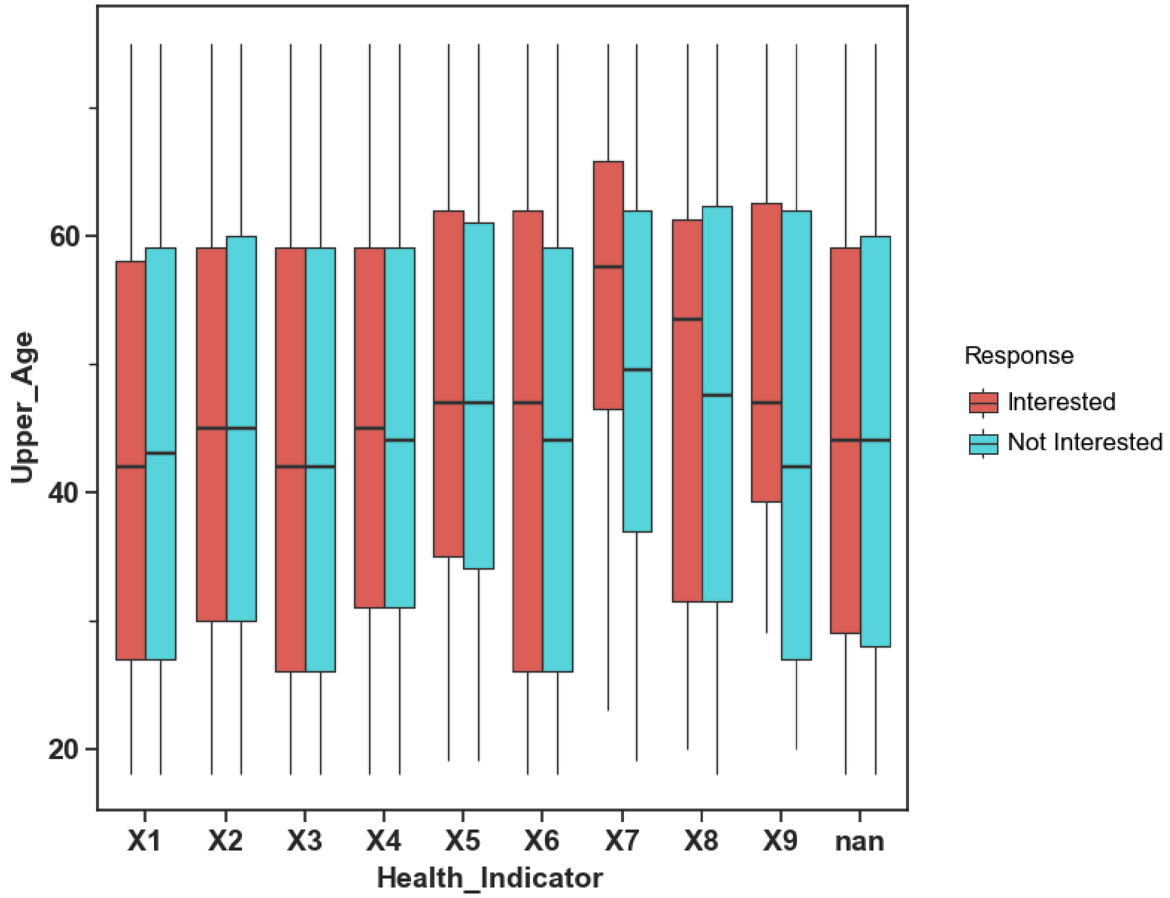
The above chart explains that from health indicator X1 to X9, customer's interest in the recommended policy is gradually decreased.

There are 11691 customers health-related information are missing.

Let's see if is there any relation between customer health indicator and customer's age. Also, check their responses to the recommended policy.

In [47]:

```
(ggplot(train)+geom_boxplot(aes(x='Health_Indicator',y='Upper_Age',fill='Response'),
 #facet_grid('Accomodation_Type~Reco_Insurance_Type')+
 theme_seaborn(style='ticks')+
theme(figure_size=(7,7),
                              axis_text=element_text(style='normal',size=14,weight='b
                              axis_title=element_text(style='normal',size=14,weight='
                              strip_text=element_text(style='normal',size=14,weight='
```



Out[47]: <ggplot: (17849341)>

In [48]:

```
train.groupby(['Health_Indicator','Response'],as_index=False).agg({'Upper_Age':['min
```

Out[48]:

	Health_Indicator	Response	Upper_Age			
			min	median	mean	max
0	X1	Interested	18	42.0	43.890113	75
1	X1	Not Interested	18	43.0	44.335977	75
2	X2	Interested	18	45.0	45.449619	75
3	X2	Not Interested	18	45.0	45.499936	75
4	X3	Interested	18	42.0	43.716073	75
5	X3	Not Interested	18	42.0	43.398799	75
6	X4	Interested	18	45.0	45.862464	75
7	X4	Not Interested	18	44.0	45.331493	75
8	X5	Interested	19	47.0	48.536765	75
9	X5	Not Interested	19	47.0	47.787718	75

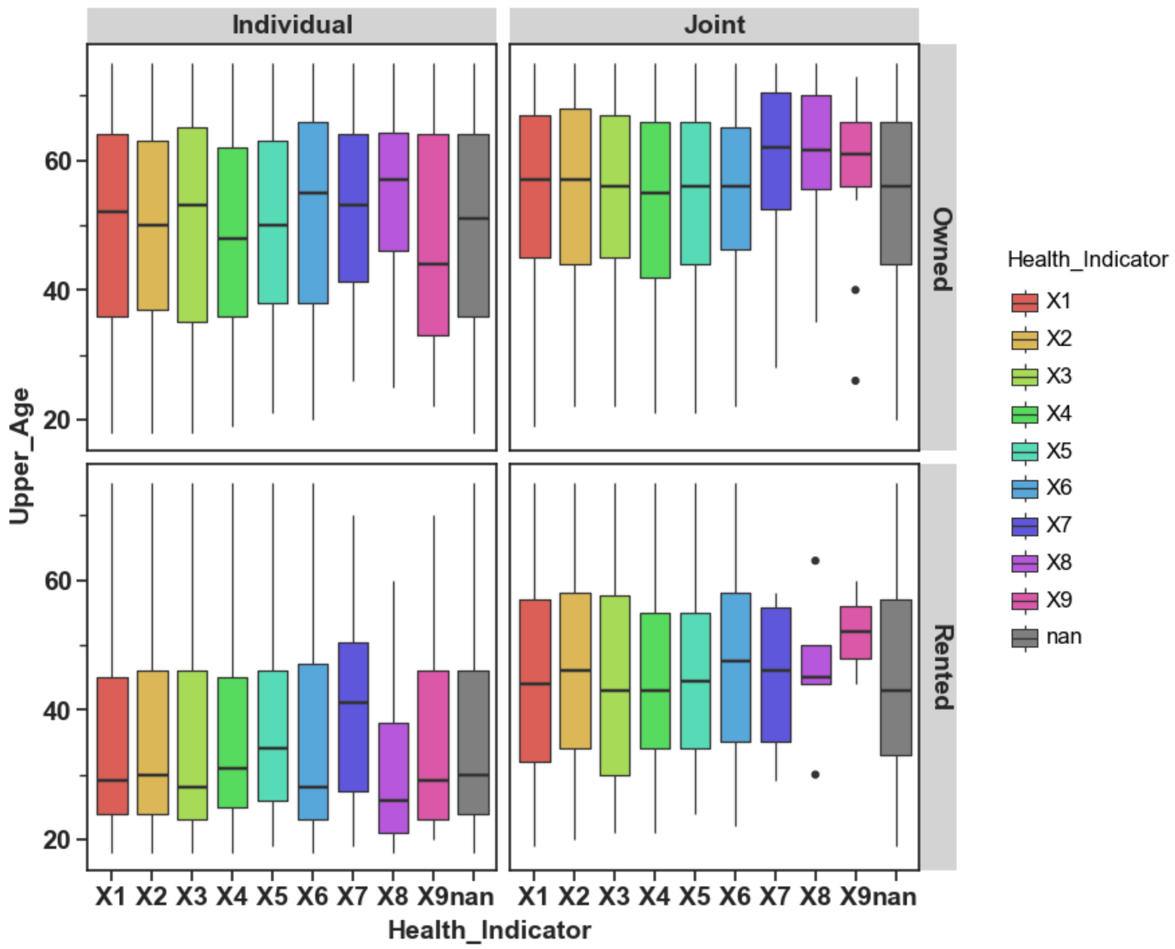
	Health_Indicator	Response	Upper_Age			
			min	median	mean	max
10	X6	Interested	18	47.0	45.342020	75
11	X6	Not Interested	18	44.0	43.789311	75
12	X7	Interested	23	57.5	54.983871	75
13	X7	Not Interested	19	49.5	49.238806	75
14	X8	Interested	20	53.5	48.555556	75
15	X8	Not Interested	18	47.5	47.083333	75
16	X9	Interested	29	47.0	49.428571	75
17	X9	Not Interested	20	42.0	44.183673	75

The above chart explains that there is a significant difference in customer's age and customer health condition indicator types.

Let's see the is there any relation between customer's age and their health condition indicator and also, cross-check those results with their recommended policy and their accommodation type.

In [49]:

```
(ggplot(train)+geom_boxplot(aes(x='Health_Indicator',y='Upper_Age',fill='Health_Indi
 facet_grid('Accomodation_Type~Reco_Insurance_Type')+
 theme_seaborn(style='ticks')+
theme(figure_size=(8,8),
                             axis_text=element_text(style='normal',size=14,weight='b
                             axis_title=element_text(style='normal',size=14,weight='
                             strip_text=element_text(style='normal',size=14,weight='
```



Out[49]: <ggplot: (17849131)>

In [50]:

```
train.groupby(['Health_Indicator','Reco_Insurance_Type','Accomodation_Type'],as_inde
```

Out[50]:

	Health_Indicator	Reco_Insurance_Type	Accomodation_Type	Upper_Age			
				min	median	mean	max
0	X1	Individual	Owned	18	52.0	50.319944	75
1	X1	Individual	Rented	18	29.0	35.491056	75
2	X1	Joint	Owned	19	57.0	55.405911	75
3	X1	Joint	Rented	19	44.0	45.631893	75
4	X2	Individual	Owned	18	50.0	49.806391	75
5	X2	Individual	Rented	18	30.0	35.908582	75
6	X2	Joint	Owned	22	57.0	55.324927	75
7	X2	Joint	Rented	20	46.0	46.602041	75
8	X3	Individual	Owned	18	53.0	50.595588	75
9	X3	Individual	Rented	18	28.0	35.131183	75
10	X3	Joint	Owned	22	56.0	55.229443	75
11	X3	Joint	Rented	21	43.0	44.426230	75
12	X4	Individual	Owned	19	48.0	48.638407	75
13	X4	Individual	Rented	18	31.0	35.980790	75

	Health_Indicator	Reco_Insurance_Type	Accomodation_Type	Upper_Age			
				min	median	mean	max
14	X4	Joint	Owned	21	55.0	54.085399	75
15	X4	Joint	Rented	21	43.0	44.854730	75
16	X5	Individual	Owned	21	50.0	50.376011	75
17	X5	Individual	Rented	19	34.0	37.234649	75
18	X5	Joint	Owned	21	56.0	55.207506	75
19	X5	Joint	Rented	24	44.5	45.631579	75
20	X6	Individual	Owned	20	55.0	51.873508	75
21	X6	Individual	Rented	18	28.0	35.615509	75
22	X6	Joint	Owned	22	56.0	55.385542	75
23	X6	Joint	Rented	22	47.5	46.736842	75
24	X7	Individual	Owned	26	53.0	51.976744	75
25	X7	Individual	Rented	19	41.0	39.978723	70
26	X7	Joint	Owned	28	62.0	58.966102	75
27	X7	Joint	Rented	29	46.0	44.750000	58
28	X8	Individual	Owned	25	57.0	54.406250	75
29	X8	Individual	Rented	18	26.0	30.680000	60
30	X8	Joint	Owned	35	61.5	59.937500	75
31	X8	Joint	Rented	30	45.0	46.400000	63
32	X9	Individual	Owned	22	44.0	46.782609	75
33	X9	Individual	Rented	20	29.0	36.920000	70
34	X9	Joint	Owned	26	61.0	58.000000	73
35	X9	Joint	Rented	44	52.0	52.000000	60

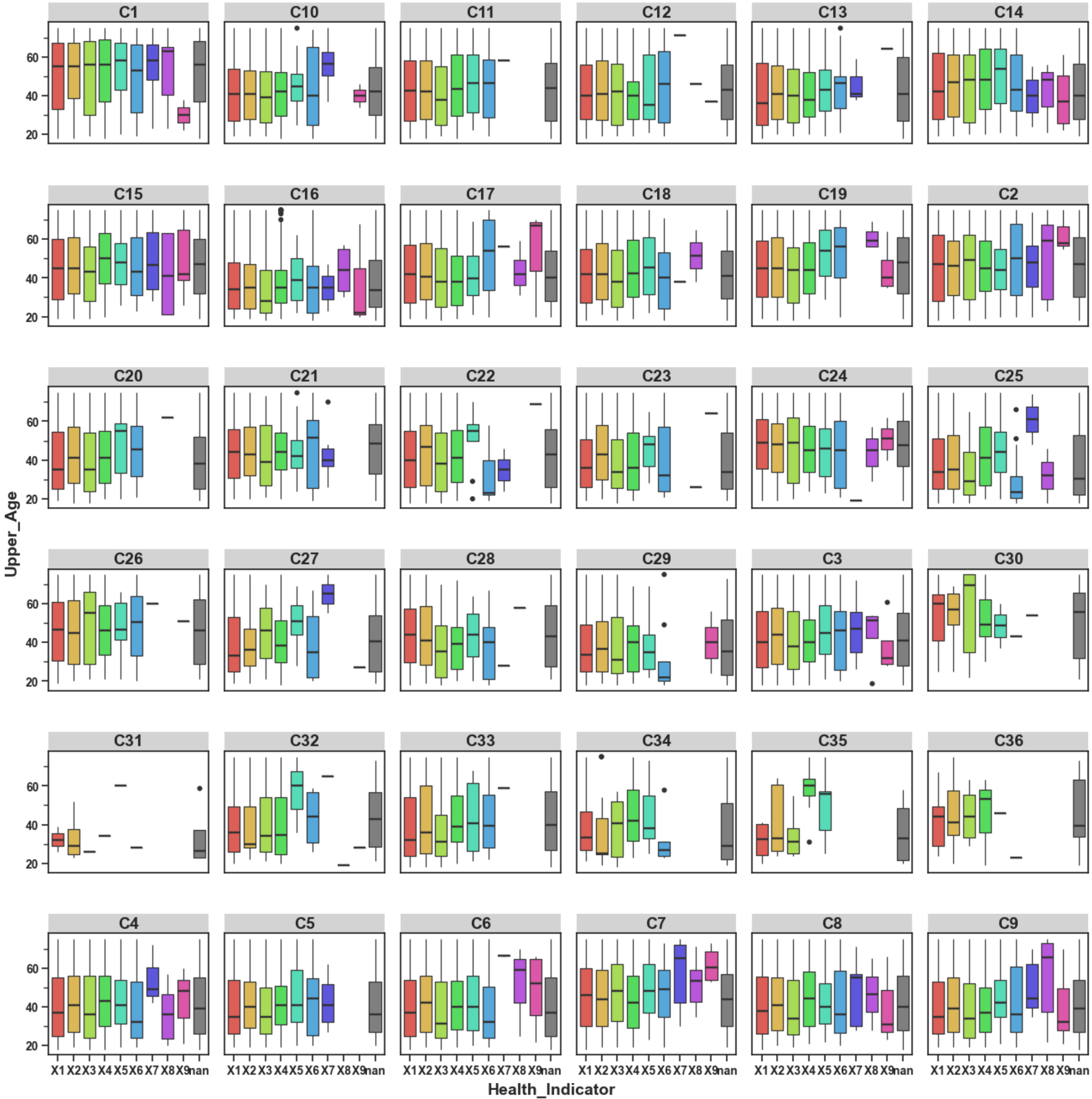
The above chart explains that the health indicator types vary with the average age of customers who are living in their own house and rent house and also recommended policy also varies based on the age.

Let's compare city and customer's health indicator types and customer's upper age.

In [51]:

```
(ggplot(train)+geom_boxplot(aes(x='Health_Indicator',y='Upper_Age',fill='Health_Indi
facet_wrap('City_Code')+
theme_seaborn(style='ticks')+
theme(figure_size=(16,16),
      legend_position='none',

subplots_adjust={'hspace': 0.5,'wspace':0.1},
axis_text=element_text(style='normal',size=10,weight='bold'),
axis_title=element_text(style='normal',size=14,weight='bold'),
strip_text=element_text(style='normal',size=14,weight='bold')))
```



Out[51]: <ggplot: (17257677)>

The average age of the customer has varied in the types of health indicators and the city in which customers are living.

Holding Policy Duration

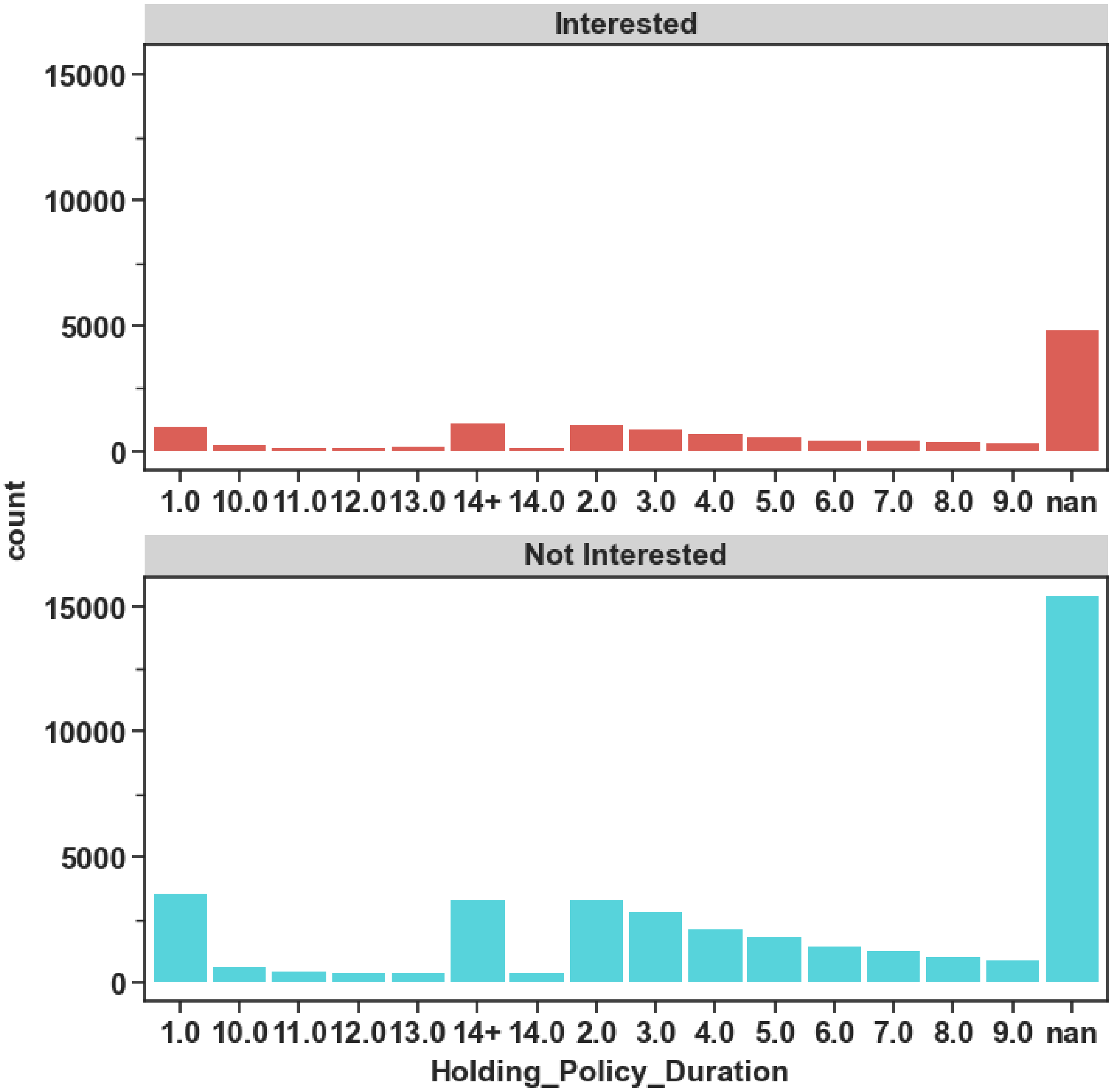
In [52]:

```
#train.groupby(['Holding_Policy_Duration','Response'],as_index=False)['Response'].ag
```

Let's see various holding policy duration which are having by customers and their responses to recommended policies.

In [53]:

```
(ggplot(train)+geom_bar(aes(x='Holding_Policy_Duration',fill='Response'), position='
theme_seaborn(style='ticks')+
facet_wrap('Response',nrow=2,scales='free_x')+
theme(figure_size=(8,8),
legend_position='none',
subplots_adjust={'hspace': 0.25,'wspace':0.1},
axis_text=element_text(style='normal',size=14,weight='bold'),
axis_title=element_text(style='normal',size=14,weight='bold'),
strip_text=element_text(style='normal',size=14,weight='bold')))
```



Out[53]: <ggplot: (12925338)>

In [54]:

```
train['Holding_Policy_Duration'].isnull().sum()
```

Out[54]: 20251

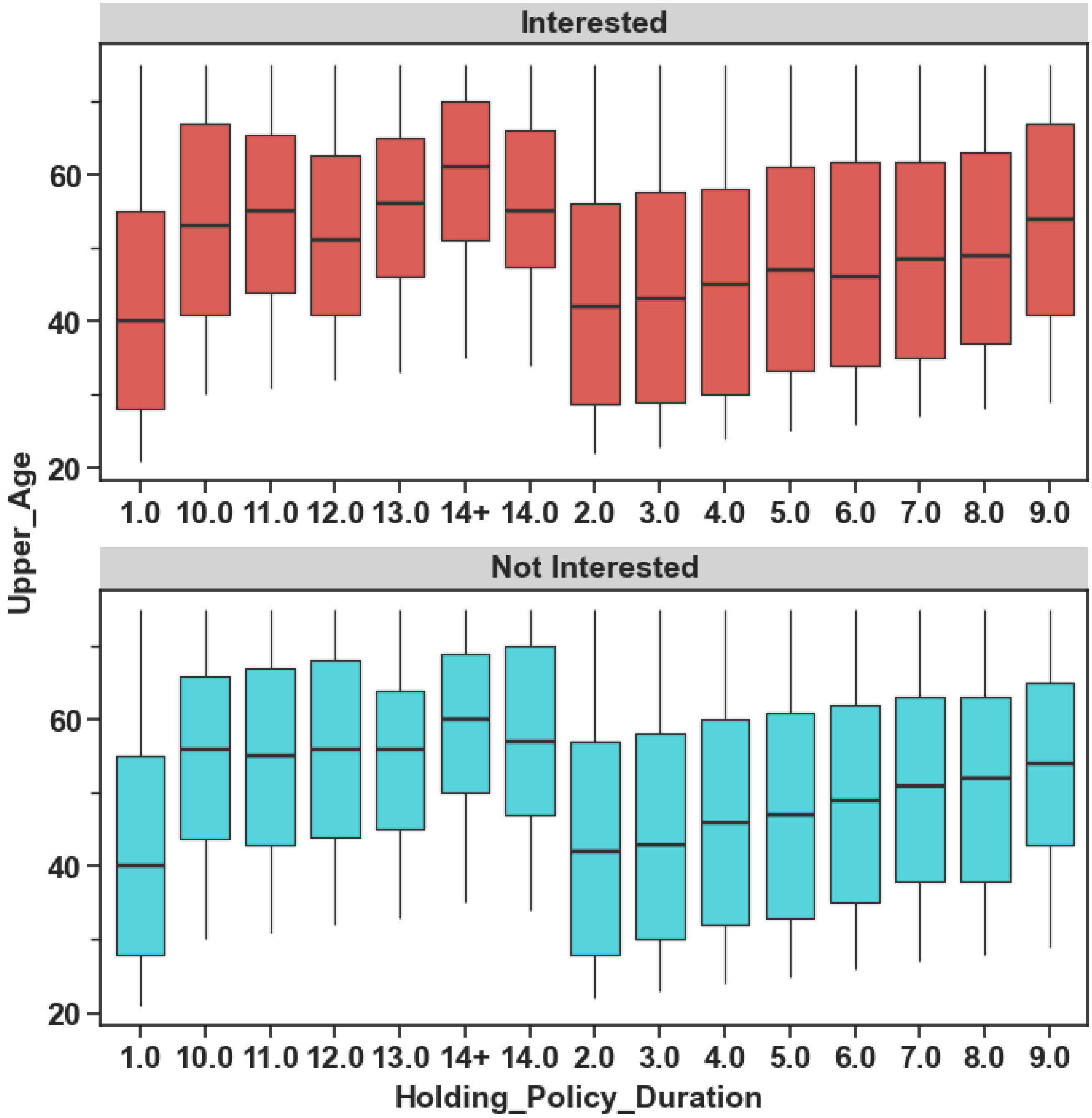
The above chart explains that customers who are holding 1 to 5 years duration policies are interested to take recommended policies.

There are 20251 customer's information of holding policy duration information is missing.

Let's see if there is a relationship between customer age and holding policy types. Then check their responses in recommended policies.

In [55]:

```
(ggplot(train.dropna())+geom_boxplot(aes(x='Holding_Policy_Duration',y='Upper_Age',f
theme_seaborn(style='ticks')+
facet_wrap('Response',nrow=2,scales='free')+
theme(figure_size=(8,8),
legend_position='none',
subplots_adjust={'hspace': 0.25,'wspace':0.1},
axis_text=element_text(style='normal',size=14,weight='bold'),
axis_title=element_text(style='normal',size=14,weight='bold'),
strip_text=element_text(style='normal',size=14,weight='bold')))
```



Out[55]: <ggplot: (-2134641804)>

In [56]:

```
train.groupby(['Holding_Policy_Duration','Response'], dropna=True,as_index = False).
```

Out[56]:

	Holding_Policy_Duration	Response	Upper_Age			
			min	median	mean	max
0	1.0	Interested	21	39.0	41.987964	75
1	1.0	Not Interested	21	40.0	42.630782	75
2	10.0	Interested	30	53.0	53.265766	75
3	10.0	Not Interested	30	55.0	54.373942	75
4	11.0	Interested	31	55.0	54.452555	75
5	11.0	Not Interested	31	56.0	54.911980	75
6	12.0	Interested	32	51.5	53.730769	75
7	12.0	Not Interested	32	56.0	55.496084	75
8	13.0	Interested	33	55.0	54.942029	75

	Holding_Policy_Duration	Response	Upper_Age			
			min	median	mean	max
9	13.0	Not Interested	33	56.0	55.857909	75
10	14+	Interested	35	60.0	59.410304	75
11	14+	Not Interested	35	60.0	59.144089	75
12	14.0	Interested	34	55.0	55.426087	75
13	14.0	Not Interested	34	59.0	58.014245	75
14	2.0	Interested	22	42.0	43.474777	75
15	2.0	Not Interested	22	41.0	43.670052	75
16	3.0	Interested	23	43.0	44.711538	75
17	3.0	Not Interested	23	44.0	45.288671	75
18	4.0	Interested	24	45.0	45.880060	75
19	4.0	Not Interested	24	46.0	46.817490	75
20	5.0	Interested	25	47.0	48.172291	75
21	5.0	Not Interested	25	47.0	47.858810	75
22	6.0	Interested	26	47.0	48.433708	75
23	6.0	Not Interested	26	50.0	49.566598	75
24	7.0	Interested	27	50.0	50.234043	75
25	7.0	Not Interested	27	50.0	50.392799	75
26	8.0	Interested	28	49.5	50.668639	75
27	8.0	Not Interested	28	51.5	51.145194	75
28	9.0	Interested	29	54.0	53.860377	75
29	9.0	Not Interested	29	53.0	53.024735	75

The above chart explains that the customers who are in the age range of 30 and above have 10 to 13-year duration policies.

21-year-old customers are having 1-year duration policies at the same time they are interested to take recommended policies.

some 35 and above age customers are having 14 years and above duration policies, they are also interested to take recommended policies same as the customers who are having 1 to 5-year duration policies.

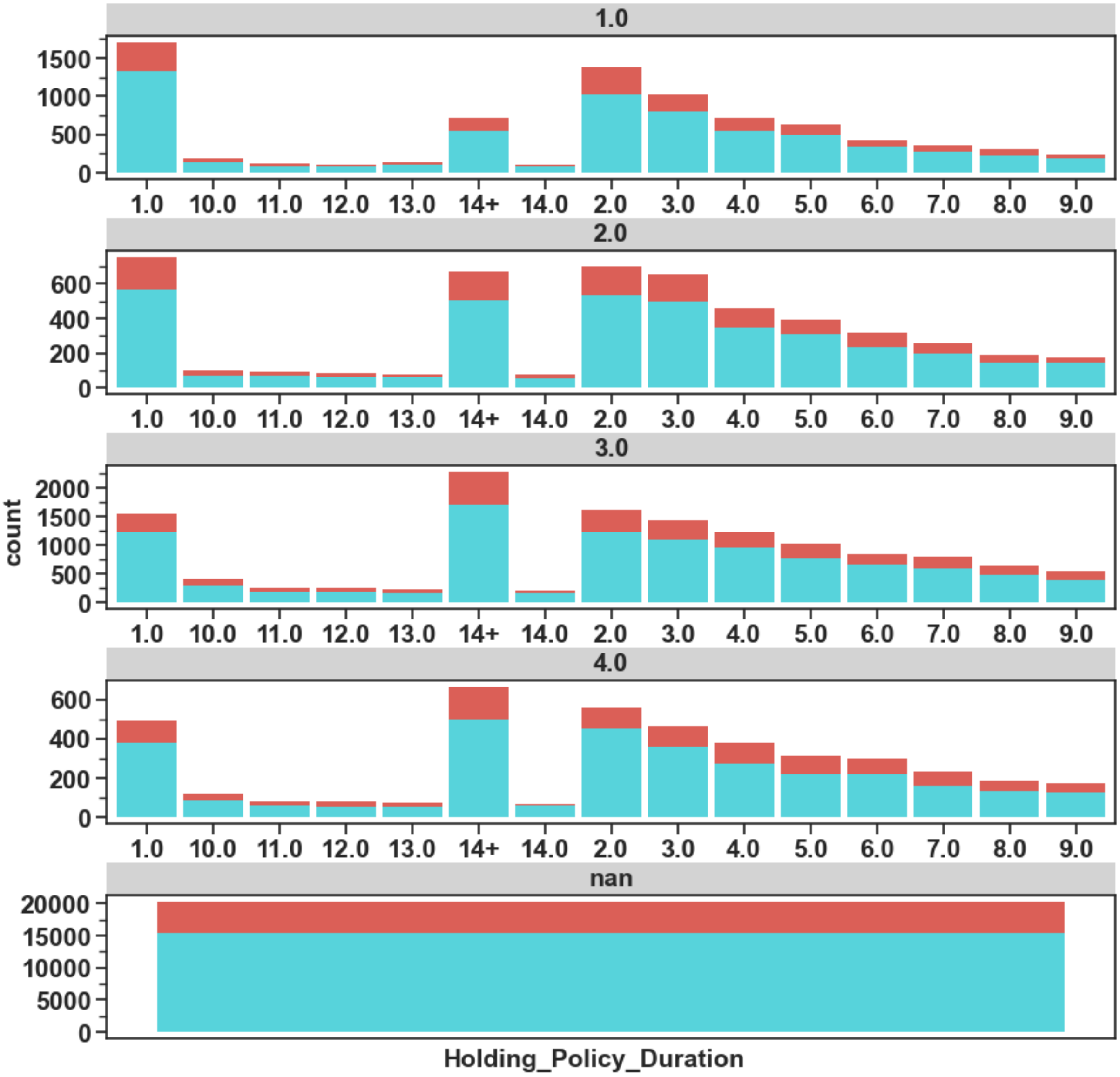
Holding Policy Type

Let's see if there is any relationship between holding policy type and its duration.

In [57]:

```
(ggplot(train)+geom_bar(aes(x='Holding_Policy_Duration',fill='Response'))+
theme_seaborn(style='ticks')+
facet_wrap('Holding_Policy_Type',nrow=5,scales='free')+
theme(figure_size=(10,10),
legend_position='none',
subplots_adjust={'hspace': 0.5,'wspace':0.1},
```

```
axis_text=element_text(style='normal',size=14,weight='bold'),
axis_title=element_text(style='normal',size=14,weight='bold'),
strip_text=element_text(style='normal',size=14,weight='bold')))
```



Out[57]: <ggplot: (-2129749478)>

In [58]:

```
train.groupby(['Holding_Policy_Type'],as_index=False)['Holding_Policy_Type'].agg({'t
```

Out[58]:

	Holding_Policy_Type	total
2	3.0	13279
0	1.0	8173
1	2.0	5005
3	4.0	4174

In [59]:

```
train['Holding_Policy_Type'].isnull().sum()
```

Out[59]: 20251

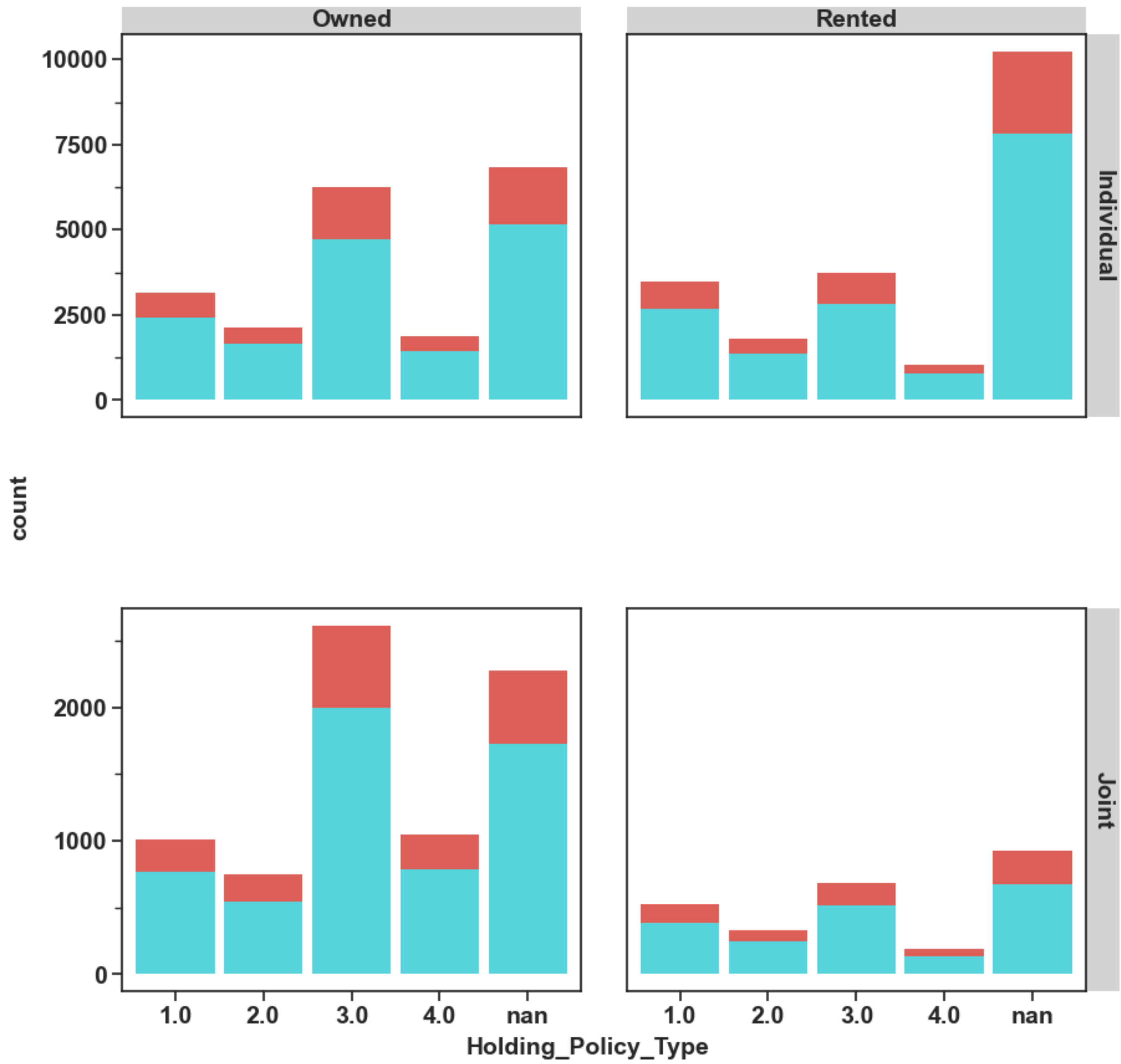
The above chart explains that each type of policy has 1 to 14 year and above duration policies.

More customers have taken the type 3 policy.

There are 20251 customer's holding policy type information are missing.

In [60]:

```
(ggplot(train.astype({'Holding_Policy_Type':'str'}))+geom_bar(aes(x='Holding_Policy_
theme_seaborn(style='ticks')+
facet_grid('Reco_Insurance_Type~Accomodation_Type',scales='free')+
theme(figure_size=(10,10),
legend_position='none',
subplots_adjust={'hspace': 0.5,'wspace':0.1},
axis_text=element_text(style='normal',size=14,weight='bold'),
axis_title=element_text(style='normal',size=14,weight='bold'),
strip_text=element_text(style='normal',size=14,weight='bold')))
```



Out[60]: <ggplot: (12943623)>

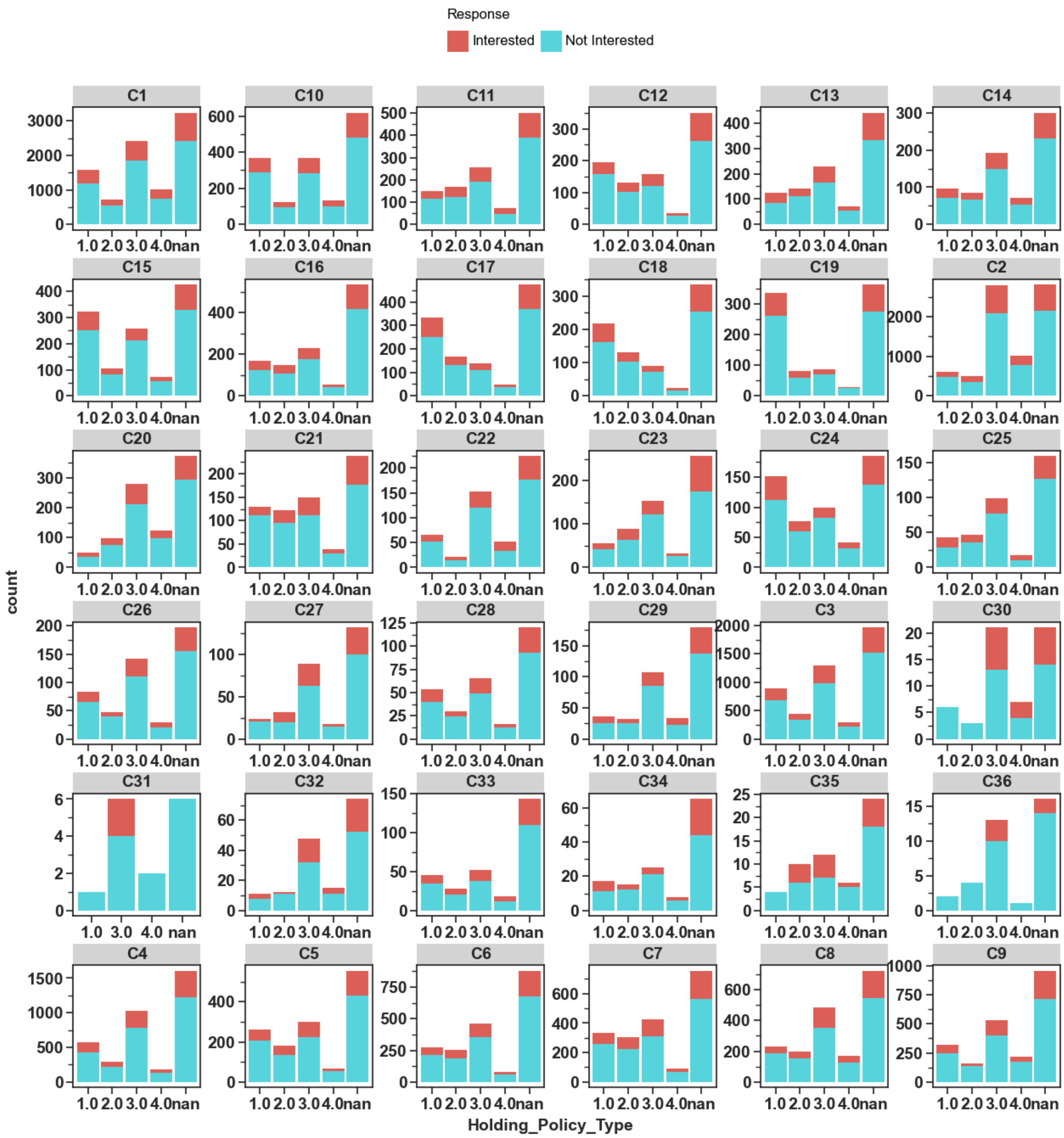
Type 3 policies are taken by more customers those customers are highly interested to take recommended policies.

Let's see city-wise customers holding policy types and their responses to the recommended policies.

In [61]:

```
(ggplot(train.astype({'Holding_Policy_Type': 'str'}))+geom_bar(aes(x='Holding_Policy
theme_seaborn(style='ticks')+
facet_wrap('City_Code',scales='free')+
theme(figure_size=(15,15),
```

```
subplots_adjust={'hspace': 0.4,'wspace':0.35},
legend_position='top',
axis_text=element_text(style='normal',size=14,weight='bold'),
axis_title=element_text(style='normal',size=14,weight='bold'),
strip_text=element_text(style='normal',size=14,weight='bold')))
```



Out[61]: <ggplot: (4013325)>

In [62]:

```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50882 entries, 0 to 50881
Data columns (total 14 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   ID                      50882 non-null  int64 
 1   City_Code               50882 non-null  object
 2   Region_Code             50882 non-null  int64 
 3   Accomodation_Type       50882 non-null  object
 4   Reco_Insurance_Type     50882 non-null  object
 5   Upper_Age               50882 non-null  int64 
 6   Lower_Age               50882 non-null  int64 
```

```
 7   Is_Spouse                50882 non-null  object
 8   Health_Indicator         39191 non-null  object
 9   Holding_Policy_Duration  30631 non-null  object
 10  Holding_Policy_Type      30631 non-null  float64
 11  Reco_Policy_Cat          50882 non-null  int64
 12  Reco_Policy_Premium      50882 non-null  float64
 13  Response                 50882 non-null  object
dtypes: float64(2), int64(5), object(7)
memory usage: 4.1+ MB
```

Test Dataset

Let's take a quick visualation of test dataset columns.

Let's see a quick view of categorical column distribution and check if there is any difference between train and test dataset categorical column levels.

In [110…

```
(ggplot(test.select_dtypes(include='object').stack().rename('value').reset_index())+
 geom_bar(aes(x='value',fill='value'))+
theme_seaborn(style='ticks')+
facet_wrap('level_1',scales='free',nrow=6)+
theme(figure_size=(15,15),
subplots_adjust={'hspace': 0.4,'wspace':0.35},
legend_position='none',
axis_text=element_text(style='normal',size=14,weight='bold'),
axis_title=element_text(style='normal',size=14,weight='bold'),
strip_text=element_text(style='normal',size=14,weight='bold')))
```

Out[110…

```
<ggplot: (-2130168662)>
```

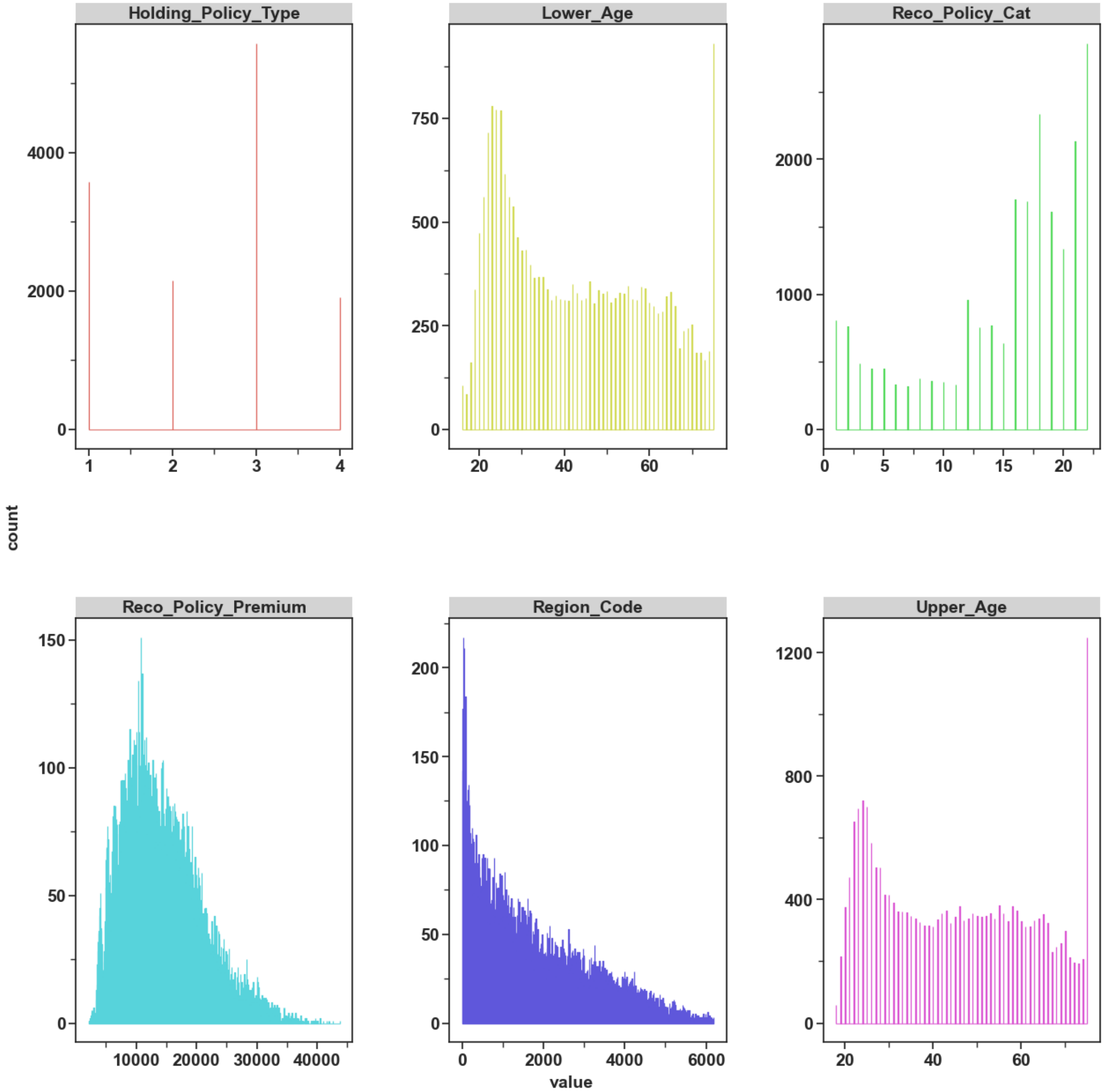
The above chart explains that there is no difference in categorical column levels between the train and test datasets.

Let's see a quick view of numerical column distribution.

In [128…

```
(ggplot(test.iloc[:,1:13].select_dtypes(exclude='object').stack().rename('value').re
 geom_histogram(aes(x='value',color='level_1'))+
theme_seaborn(style='ticks')+
facet_wrap('level_1',scales='free')+
theme(figure_size=(15,15),
subplots_adjust={'hspace': 0.4,'wspace':0.35},
legend_position='none',
axis_text=element_text(style='normal',size=14,weight='bold'),
axis_title=element_text(style='normal',size=14,weight='bold'),
strip_text=element_text(style='normal',size=14,weight='bold')))
```

```
C:\Users\Balaji\AppData\Local\Programs\Python\Python38-32\lib\site-packages\plotnine
\stats\stat_bin.py:93: PlotnineWarning: 'stat_bin()' using 'bins = 604'. Pick better
value with 'binwidth'.
```



Out[128… <ggplot: (-2129994931)>

So far we have done exploratory data analysis in various way ,

- **Univariate Analysis**
- **Bi-Variate Analysis**
- **Multi_Variate Analysis**

This analysis tells that the customers who are living in the city C1 to C10 and having their own house are highly interested to take recommended policies.

Individual policy is recommended to most customers and those customers are highly interested to take it.

Customers who are in the age of 20 to '30s and living in a rented house are interested to take recommended policies when compared to the same age group customers who are living in the own house.