

In [1]:

```
print("Name: RAMISETTY PAVANI")  
print("Registration Number: 21BCE9521")  
print("Morning Batch")
```

Name: RAMISETTY PAVANI  
Registration Number: 21BCE9521  
Morning Batch

In [2]:

```
import seaborn as sns  
import matplotlib.pyplot as plt
```

In [3]:

```
df=sns.load_dataset('car_crashes')
```

In [4]:

```
df
```

Out[4]:

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses	abbrev
0	18.8	7.332	5.640	18.048	15.040	784.55	145.08	AL
1	18.1	7.421	4.525	16.290	17.014	1053.48	133.93	AK
2	18.6	6.510	5.208	15.624	17.856	899.47	110.35	AZ
3	22.4	4.032	5.824	21.056	21.280	827.34	142.39	AR
4	12.0	4.200	3.360	10.920	10.680	878.41	165.63	CA
5	13.6	5.032	3.808	10.744	12.920	835.50	139.91	CO
6	10.8	4.968	3.888	9.396	8.856	1068.73	167.02	CT
7	16.2	6.156	4.860	14.094	16.038	1137.87	151.48	DE
8	5.9	2.006	1.593	5.900	5.900	1273.89	136.05	DC
9	17.9	3.759	5.191	16.468	16.826	1160.13	144.18	FL
10	15.6	2.964	3.900	14.820	14.508	913.15	142.80	GA
11	17.5	9.450	7.175	14.350	15.225	861.18	120.92	HI
12	15.3	5.508	4.437	13.005	14.994	641.96	82.75	ID
13	12.8	4.608	4.352	12.032	12.288	803.11	139.15	IL
14	14.5	3.625	4.205	13.775	13.775	710.46	108.92	IN
15	15.7	2.669	3.925	15.229	13.659	649.06	114.47	IA
16	17.8	4.806	4.272	13.706	15.130	780.45	133.80	KS
17	21.4	4.066	4.922	16.692	16.264	872.51	137.13	KY
18	20.5	7.175	6.765	14.965	20.090	1281.55	194.78	LA
19	15.1	5.738	4.530	13.137	12.684	661.88	96.57	ME
20	12.5	4.250	4.000	8.875	12.375	1048.78	192.70	MD
21	8.2	1.886	2.870	7.134	6.560	1011.14	135.63	MA
22	14.1	3.384	3.948	13.395	10.857	1110.61	152.26	MI
23	9.6	2.208	2.784	8.448	8.448	777.18	133.35	MN
24	17.6	2.640	5.456	1.760	17.600	896.07	155.77	MS
25	16.1	6.923	5.474	14.812	13.524	790.32	144.45	MO
26	21.4	8.346	9.416	17.976	18.190	816.21	85.15	MT
27	14.9	1.937	5.215	13.857	13.410	732.28	114.82	NE
28	14.7	5.439	4.704	13.965	14.553	1029.87	138.71	NV
29	11.6	4.060	3.480	10.092	9.628	746.54	120.21	NH
30	11.2	1.792	3.136	9.632	8.736	1301.52	159.85	NJ
31	18.4	3.496	4.968	12.328	18.032	869.85	120.75	NM
32	12.3	3.936	3.567	10.824	9.840	1234.31	150.01	NY
33	16.8	6.552	5.208	15.792	13.608	708.24	127.82	NC
34	23.9	5.497	10.038	23.661	20.554	688.75	109.72	ND
35	14.1	3.948	4.794	13.959	11.562	697.73	133.52	OH
36	19.9	6.368	5.771	18.308	18.706	881.51	178.86	OK
37	12.8	4.224	3.328	8.576	11.520	804.71	104.61	OR
38	18.2	9.100	5.642	17.472	16.016	905.99	153.86	PA
39	11.1	3.774	4.218	10.212	8.769	1148.99	148.58	RI
40	23.9	9.082	9.799	22.944	19.359	858.97	116.29	SC
41	19.4	6.014	6.402	19.012	16.684	669.31	96.87	SD
42	19.5	4.095	5.655	15.990	15.795	767.91	155.57	TN
43	19.4	7.760	7.372	17.654	16.878	1004.75	156.83	TX
44	11.3	4.859	1.808	9.944	10.848	809.38	109.48	UT
45	13.6	4.080	4.080	13.056	12.920	716.20	109.61	VT
46	12.7	2.413	3.429	11.049	11.176	768.95	153.72	VA
47	10.6	4.452	3.498	8.692	9.116	890.03	111.62	WA
48	23.8	8.092	6.664	23.086	20.706	992.61	152.56	WV
49	13.8	4.968	4.554	5.382	11.592	670.31	106.62	WI

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses	abbrev
In [5]:	18.8	7.308	5.568	14.094	15.660	791.14	122.04	WY

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51 entries, 0 to 50
Data columns (total 8 columns):
#   Column                Non-Null Count  Dtype
---  -
0   total                  51 non-null    float64
1   speeding               51 non-null    float64
2   alcohol                51 non-null    float64
3   not_distracted         51 non-null    float64
4   no_previous            51 non-null    float64
5   ins_premium            51 non-null    float64
6   ins_losses             51 non-null    float64
7   abbrev                 51 non-null    object
dtypes: float64(7), object(1)
memory usage: 3.3+ KB
```

In [6]:

```
df.head(9)
```

Out[6]:

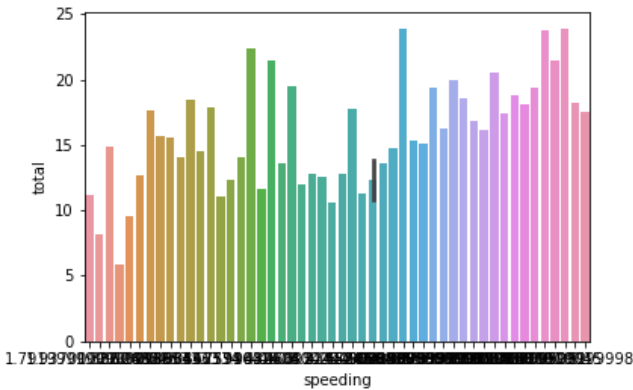
	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses	abbrev
0	18.8	7.332	5.640	18.048	15.040	784.55	145.08	AL
1	18.1	7.421	4.525	16.290	17.014	1053.48	133.93	AK
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3	22.4	4.032	5.824	21.056	21.280	827.34	142.39	AR
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6	10.8	4.968	3.888	9.396	8.856	1068.73	167.02	CT
7	16.2	6.156	4.860	14.094	16.038	1137.87	151.48	DE
8	5.9	2.006	1.593	5.900	5.900	1273.89	136.05	DC

In [7]:

```
sns.barplot(x='speeding', y='total', data=df)
```

Out[7]:

<AxesSubplot:xlabel='speeding', ylabel='total'>



In [8]:

```
print("Inference: From the plot we can say that as speed increases the total car crashes are increasing")
```

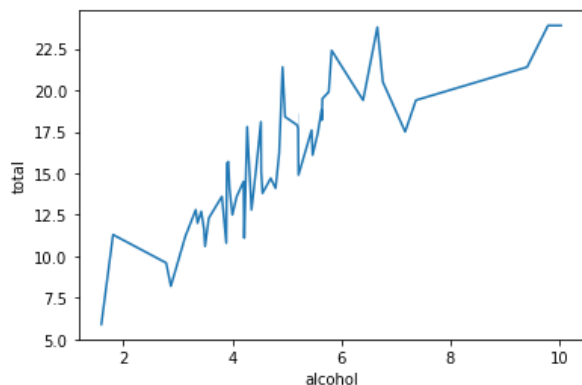
Inference: From the plot we can say that as speed increases the total car crashes are increasing

In [9]:

```
sns.lineplot(x='alcohol', y='total', data=df)
```

Out[9]:

<AxesSubplot:xlabel='alcohol', ylabel='total'>



In [10]:

```
print("Inference: From the plot we can say that as consumption of alcohol increases the total car crashes are increasing")
```

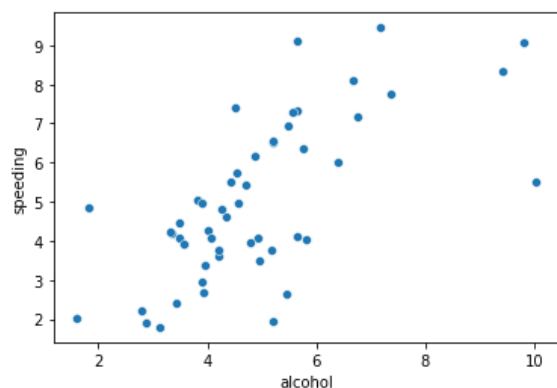
Inference: From the plot we can say that as consumption of alcohol increases the total car crashes are increasing

In [11]:

```
sns.scatterplot(x='alcohol', y='speeding', data=df)
```

Out[11]:

<AxesSubplot:xlabel='alcohol', ylabel='speeding'>



In [12]:

```
print("Inference: From the plot we can say that as consumption of alcohol increases the speed is increasing")
```

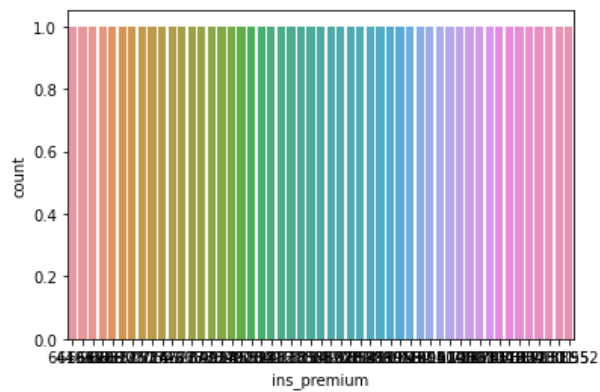
Inference: From the plot we can say that as consumption of alcohol increases the speed is increasing

In [13]:

```
sns.countplot(x='ins_premium', data=df)
```

Out[13]:

<AxesSubplot:xlabel='ins\_premium', ylabel='count'>



In [14]:

```
print("Inference: From the plot we can see the count of insurance premium cars")
```

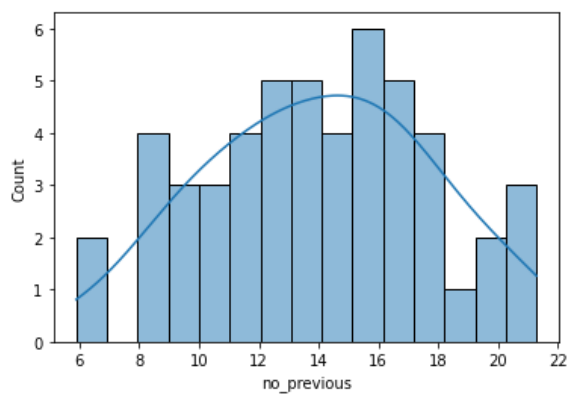
Inference: From the plot we can see the count of insurance premium cars

In [15]:

```
sns.histplot(df["no_previous"], kde=True, bins=15)
```

Out[15]:

<AxesSubplot:xlabel='no\_previous', ylabel='Count'>



In [16]:

```
print("Inference: From the plot we can say the count of no.of previous car craches")
```

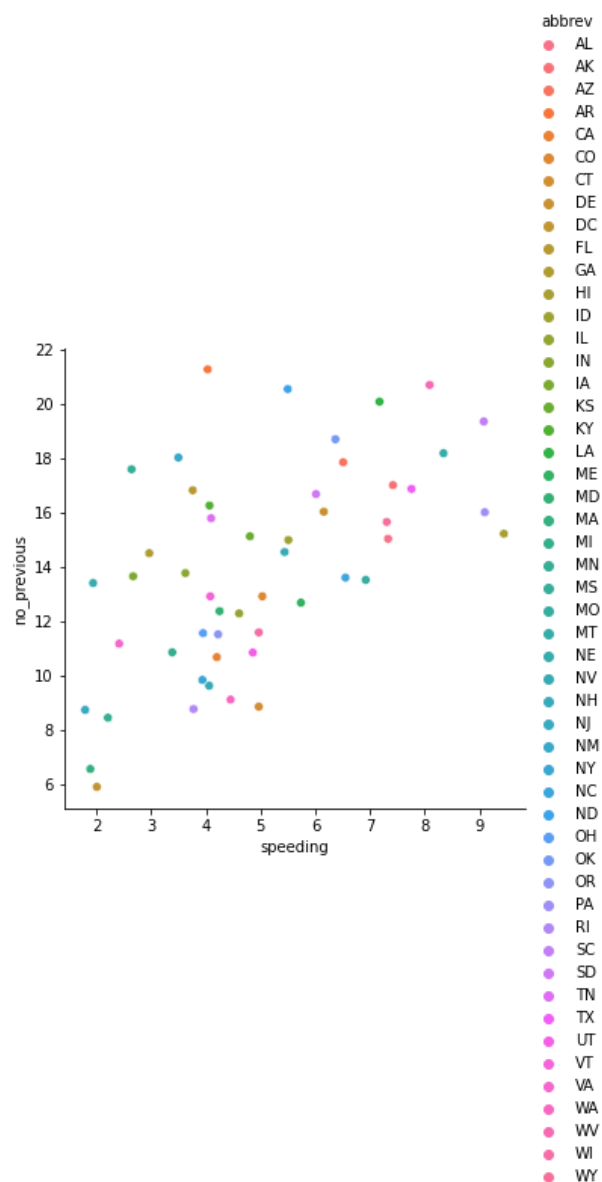
Inference: From the plot we can say the count of no.of previous car craches

In [17]:

```
sns.relplot(x='speeding', y='no_previous', data=df, hue='abbrev')
```

Out[17]:

```
<seaborn.axisgrid.FacetGrid at 0x22fa894d8b0>
```



In [18]:

```
print("Inference: From the plot we can see the relation between speeding and no.of previous car crashes with respect to abbrev")
```

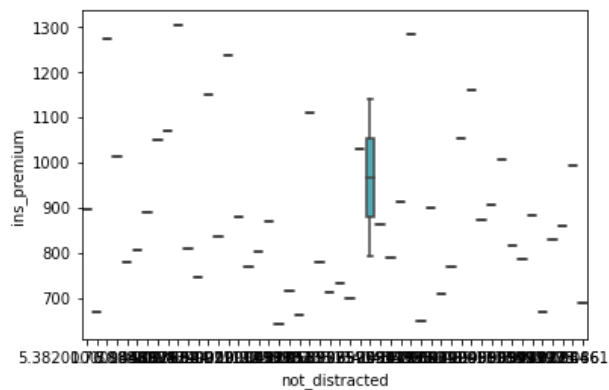
Inference: From the plot we can see the relation between speeding and no.of previous car crashes with respect to abbrev

In [19]:

```
sns.boxplot(x='not_distracted',y='ins_premium', data=df)
```

Out[19]:

```
<AxesSubplot:xlabel='not_distracted', ylabel='ins_premium'>
```



In [20]:

```
print("Inference: From the plot we can see the non distracted cars with insurance premium")
```

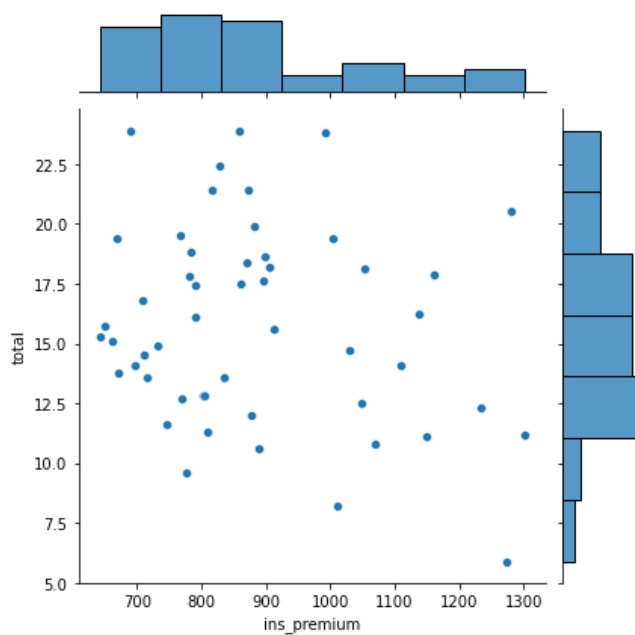
Inference: From the plot we can see the non distracted cars with insurance premium

In [21]:

```
sns.jointplot(x="ins_premium",y="total",data=df)
```

Out[21]:

```
<seaborn.axisgrid.JointGrid at 0x22fa90c75b0>
```



In [22]:

```
print("Inference: From the plot we can see no.of insurance premium cars tend to car crash")
```

Inference: From the plot we can see no.of insurance premium cars tend to car crash

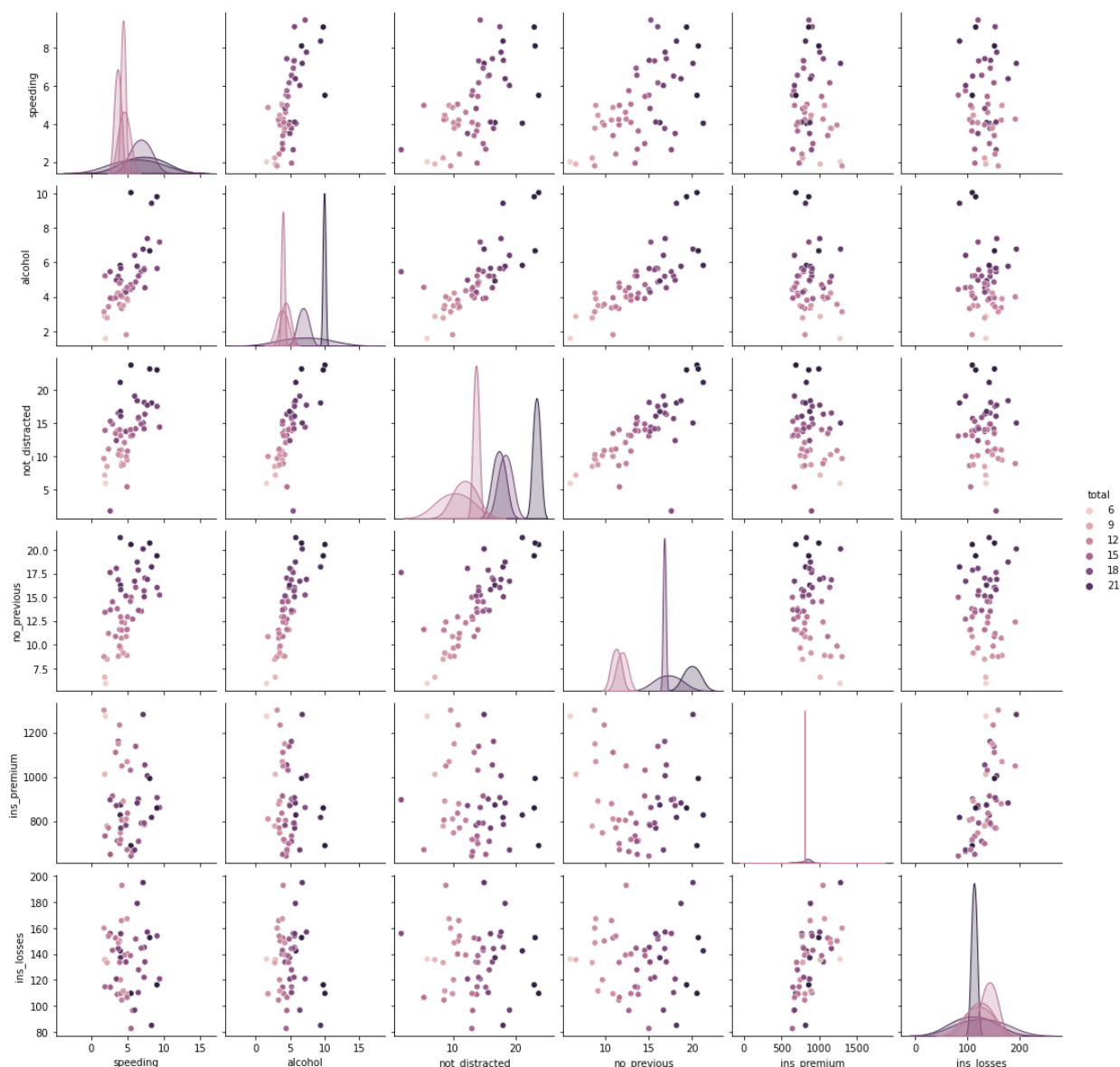


In [23]:

```
sns.pairplot(df.select_dtypes(['number']), hue='total')
```

Out[23]:

&lt;seaborn.axisgrid.PairGrid at 0x22fa9254e80&gt;



In [24]:

```
print("Inference: From the plot we can see the different variables plotted against each other. And when plotted with same
```

Inference: From the plot we can see the different variables plotted against each other. And when plotted with the same variable we can see a straight line indicating correlation=1

In [25]:

```
corr=df.corr()
corr
```

Out[25]:

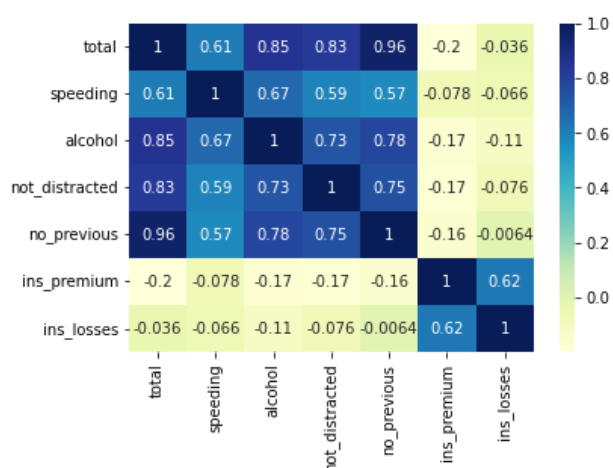
	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses
total	1.000000	0.611548	0.852613	0.827560	0.956179	-0.199702	-0.036011
speeding	0.611548	1.000000	0.669719	0.588010	0.571976	-0.077675	-0.065928
alcohol	0.852613	0.669719	1.000000	0.732816	0.783520	-0.170612	-0.112547
not_distracted	0.827560	0.588010	0.732816	1.000000	0.747307	-0.174856	-0.075970
no_previous	0.956179	0.571976	0.783520	0.747307	1.000000	-0.156895	-0.006359
ins_premium	-0.199702	-0.077675	-0.170612	-0.174856	-0.156895	1.000000	0.623116
ins_losses	-0.036011	-0.065928	-0.112547	-0.075970	-0.006359	0.623116	1.000000

In [26]:

```
sns.heatmap(corr,annot=True, cmap="YlGnBu")
```

Out[26]:

&lt;AxesSubplot:&gt;



In [27]:

```
print("Inference: The dark color indicates the corresponding variables are highly correlated where as light color indicates the variables are less correlated with each other. And diagonal is always 1 because each variable is correlated with itself")
```

Inference: The dark color indicates the corresponding variables are highly correlated where as light color indicates the variables are less correlated with each other. And diagonal is always 1 because each variable is correlated with itself