# Conspiracy and Mental Well-Being: A Dynamic Network Analysis

Bachelor's Project Thesis

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**Abstract:**

**Background**
With the COVID-19 pandemic creating the potential circumstances for a bloom in conspiracy theories, understanding the functionality of conspiracy's development is of a heightened importance. The existing literature is mixed on whether conspiracy is a cause or a symptom of negative mental well-being, with some studies suggesting it may be a coping mechanism resulting in potential improvements to mental well-being. Network analysis is a relatively new approach in psychopathology that has led to fresh insights in the complex organisation of disorders. By applying it here, the connections between conspiracy and mental well-being can be visualised and studied in a previously unexplored manner.

**Methods**
This paper used data on 2942 participants collected by the Psycorona Initiative. Their weekly responses were used to create a multi-level vector auto-regression model from which dynamic networks could be generated. This allowed the temporal associations across weeks, as well as the between subjects relationships, of conspiracy and other psychological factors to be investigated.

**Results**
From the networks, further evidence was found for the co-morbidity of conspiracy and negative mental-well being. The temporal network indicated that conspiracy acts as a driver of paranoia, which in turn is causally related to lower happiness and satisfaction. Additionally conspiracy appears to causally propagate itself across time. No statistically significant effect of mental well-being on conspiracy was seen, and across the networks conspiracy scored low on measures of centrality.

**Conclusion**
In addition to reinforcing the link between conspiracy and negative mental well-being, this project presents evidence that conspiracy may be a cause and not an effect of negative mental well-being. Conspiracy's low centrality and strong self-reinforcement could indicate that it is being driven by factors unrelated to mental well-being, beyond the scope of this network analysis.

## 1 Introduction

A conspiracy theory may be defined as a belief that, hidden from the public, powerful groups are operating to covertly and malevolently influence the world (Bale, 2007). A study in the United States found that at least 50% of Americans believe in at least one conspiracy theory, with almost 20% believing in multiple (Oliver & Wood, 2014), with very similar results found for Europeans (Naughton, 2019). Conspiracy theories have real consequences for people's health, relationships, and safety, and appear to be universal, in that they transcend cultural and social boundaries (van Prooijen & Douglas, 2018). The main drivers of conspiracy are epistemic (understanding of one's environment), and existential (feeling safe and in control of one's environment) (Douglas, Sutton, & Cichocka, 2017).

The COVID-19 pandemic, officially declared a global pandemic in March 2020, has had a negative effect on the mental health and well-being of many (Bhattarai & Karki, 2020). With a novel and complex threat, conditions are prime for conspiracy to take off. Gaining a good understanding of conspiracy thus becomes vital, as belief in conspiracy can affect one's behaviour (Karić & Međedović, 2021), which may prove lethal when combined with a pandemic. While we know that conspiracy is associated with negative mental well-being, evidence is mixed for whether it is a cause or effect of negative mental well-being, with some research suggesting it may act as a coping mechanism, resulting in improvements in mental well-being (van Prooijen & Douglas, 2018).

A suitable tool for investigating these questions is a network analysis. Inspired by the Granger causal models of economics, it allows for the interaction between a host of variables to be conceptualised as a causally connected system (Borsboom & Cramer, 2013). Thus, the causal interplay between mental well-being and conspiracy can be visualised and better analysed. For this, multi-level vector autoregression (mlVAR) modelling is well suited. It is highly flexible, predictive, and has been used to considerable effect in macroeconomics (Toda & Phillips, 1991). With mlVAR, a causal temporal and a between subjects effects network can be generated. From these the risk factors of conspiracy, along with its cause and effects in mental well-being can be clearly analysed by examining the topology and centrality of the networks. Additionally the existence of potentially influential missing nodes, representing forces outside mental well-being, can be identified (Eichler, 2007).

Not only is a network analysis well suited for the mapping and exploration of complex psychological systems, it may also aid in improving them. Researchers are currently looking into network control theory, essentially attempting to manipulate these brain networks, to treat problems such as Major Depressive Disorder (Hahn, Jamalabadi, et al., 2021; Hahn, Winter, et al., 2021). By identifying influential nodes, the factors they represent can be targeted to mitigate their negative effects.

In order to do this, data from Psycorona will be used. This was a longitudinal survey study that gathered data on over 60,000 respondents across the world, starting in March 2020. The project collected information on the cognitive, behavioural, and emotional responses of participants during the pandemic, including a set of questions aimed to measure conspiracy.

# 2 Methodology

**Psycorona data**

Of the many factors tracked by the Psycorona initiative over the course of their study, the ones of relevance here are: *Hope, Loneliness, Paranoia, Inspiration, Excitement, Nervousness, Anxiety, Calm, Happiness, Satisfaction, Relaxation, Boredom, Depression, Exhaustion, Energetic,* and *Conspiracy.* These measures tracked cognitive and emotional states related to mental well-being, and in the case of *Conspiracy* our focus, conspiracy. Variables fall into two categories; cognitive and psychological, with cognitive covering *Conspiracy* and *Paranoia*, and the rest falling under psychological. Psychological variables were measured through direct testing on a 7 point Likert scale. An example question being "How relaxed did you feel in the last week?". The cognitive variables were measured similarly but through indirect questions, such as "how much do you agree with the statement: the government is withholding information from the public."

2942 participants were selected. These participants had completed at least 10 weeks of the survey study on the relevant 16 variables. Further demographic information on this subset of the Psycorona respondents can be found in Appendix A.

**Preprocessing**

To avoid redundancy from highly correlated variables, groups of variables were generated via $k$-means clustering. To find the optimal number of clusters, both the total within sum of squares and the gap statistic were graphed. As both of these proved inconclusive, the clustering for each value of $k$ was manually investigated. A value of 5 was chosen, as below this the clustering no longer made logical sense. This resulted in the following clusters: a positive group containing *Hope, Inspiration, Energetic, Excitement, Calm*, and *Relaxation.* A negative group containing *Loneliness, Nervousness, Anxiety, Boredom, Depression,* and *Exhaustion.* A group containing the pair *Happiness* and *Satisfaction*, and finally two solo variables *Paranoia*, and *Conspiracy*, for a total of five clusters. Values in each group were averaged for each respondent and time point, with missing values being replaced by the mean of that variable up to that point in time. This creates a full multivariate time series of our five clusters for mlVAR while aiming to maintain accuracy (Jordan, Winer, & Salem, 2020a).

**Statistical analyses**

The main analysis was conducted with a multi-level vector autoregressive model. This estimated two networks, a within person temporal network, and a between-subjects effects network. Each were computed through node-wise multi-level regression, using orthogonal estimation, as recommended for networks with this many nodes (Epskamp, Waldorp, Mõttus, & Borsboom, 2018). The temporal network (results of which are shown in Figure 3.2) represents estimations of lag-1 causal relationships, with lag-1 in this case representing one week, that indicate if a node predicts another. This is visualised as directed edges between nodes, and will represent the causes and effects of conspiracy and mental well-being. The between-subjects network (Figure 3.1) visualises the connection between variables based on the means for each respondent. It can estimate the chance of variables appearing together, representing which aspects of mental well-being serve as risk factors for conspiracy or vice-versa. All analysis is performed in R, with modelling done via the *mlVAR* package.

**Visualisation**

All graphs are created through the *qgraph* package. In the networks, blue and red edges represent positive and negative connections respectively. The thickness and darkness of an edge is scaled to the relative strength of the connection in the network, thus the thickest darkest edge is the strongest connection. Nodes consist of the clusters of variables obtained earlier, and are divided into two coloured categories. Light blue nodes represent psychological variables; the *positive group*, *negative group*, and *happiness and satisfaction.* Light orange nodes represent cognitive variables; *conspiracy* and *paranoia.* Positive mental well-being is captured in the *positive group* and *happiness and satisfaction* nodes, negative mental well-being in the *negative group* and *paranoia* nodes, while conspiracy itself is covered by its namesake. As opposed to in the undirected between-subjects network, edges also have direction in the temporal effects network, represented by an arrowhead indicating the flow of causality.

# 3 Results

**Network Analysis**

To first gain an understanding of the general connections between conspiracy and mental well-being, we begin with the between-subjects network (Figure 3.1). This visualises which variables appear together across the sampled population. At the top we see unsurprisingly that higher levels in the *positive group* of emotions and *happiness and satisfaction* are strongly correlated, with both being negatively correlated with the *negative group* of emotions. The *negative group* is also connected to *conspiracy* and *paranoia*, with *paranoia* in turn also connected to *conspiracy.* This suggests that poor mental well-being can be a risk factor for conspiratorial thinking or vice versa, lining up with previous research on conspiracy and poor mental health (van Prooijen & Douglas, 2018; Oliver & Wood, 2014).

Moving onto the temporal effects network (Figure 3.2), we see which variables predict others the following week, giving us insight into the causes and effects between conspiracy and mental well-being. The strongest connections are self-reinforcing. Positive and negative mental well-being appear to be causally connected to the same state of well-being the following week. Conspiracy in particular also shows this self-reinforcement. This may indicate that conspiracy is being influenced by external forces not accounted for in the network (Eichler, 2007). It could also signify that conspiracy is simply self perpetuating, with conspiracy at a time point driving conspiracy the following week. To better visualise the causal relationship between conspiracy and mental well-being, we can take the temporal effects network

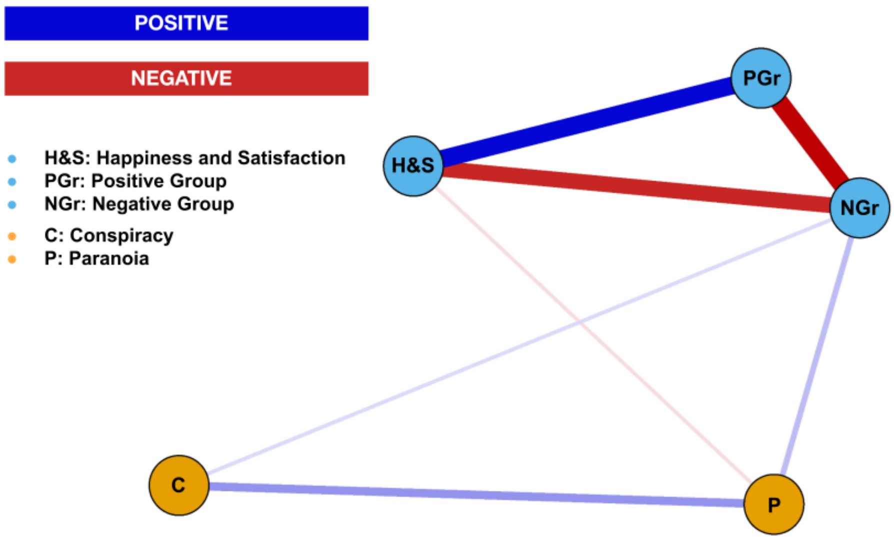


**Figure 3.1: Undirected Between-subjects effects network. Edges represent strength of connection between variables, stronger connections show higher correlation and synchronicity. Psychological and cognitive nodes are in light blue and orange respectively.**

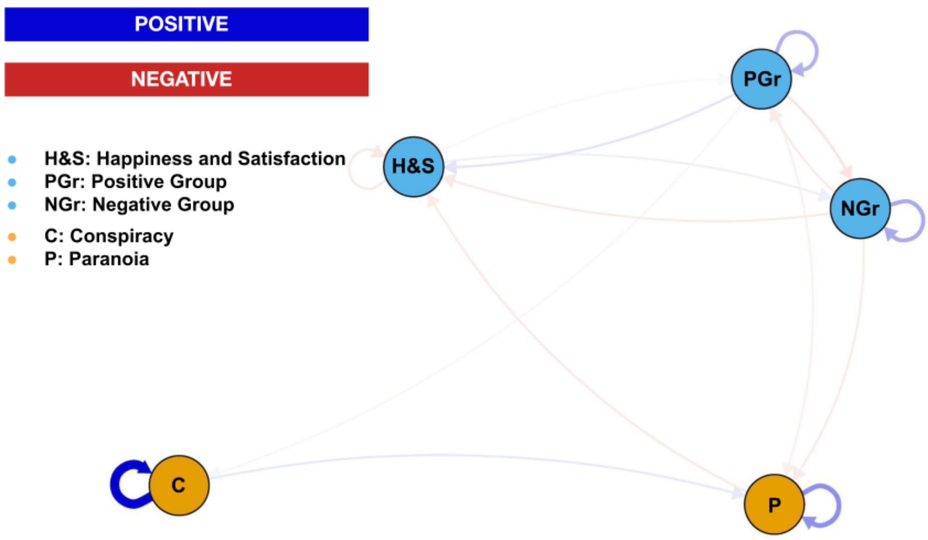


**Figure 3.2: Directed temporal effects network. Edges represent an estimate of cause and effect, with arrows showing direction of causality. Strength of connection (how pronounced the edge is) represent how strongly a node predicts the node downstream. Psychological and cognitive nodes are in light blue and orange respectively.**

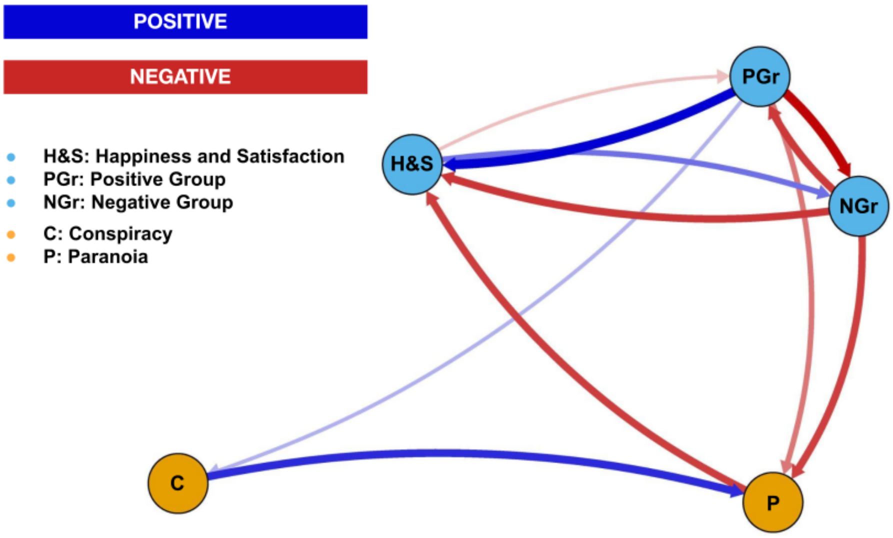


**Figure 3.3: Directed temporal effects network with self reinforcement loops removed and between node effects scaled up. Edges represent an estimate of cause and effect, with arrows showing direction of causality. Strength of connection (how pronounced the edge is) represent how strongly a node predicts the node downstream. Psychological and cognitive nodes are in light blue and orange respectively.**

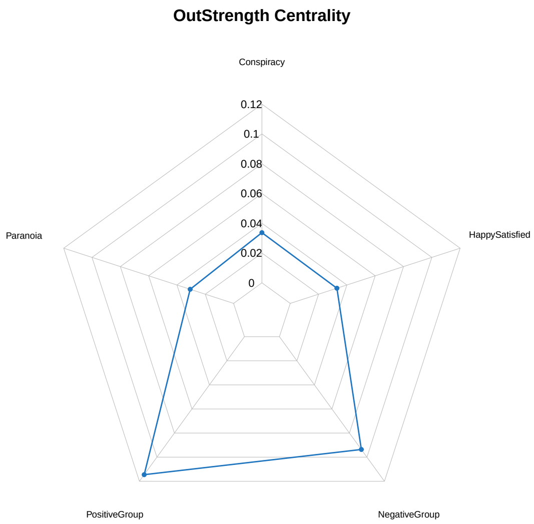


**Figure 3.4: Radar chart of the OutStrength centrality (the sum of all outgoing absolute edge weights from a node) of the variables in the temporal network.**

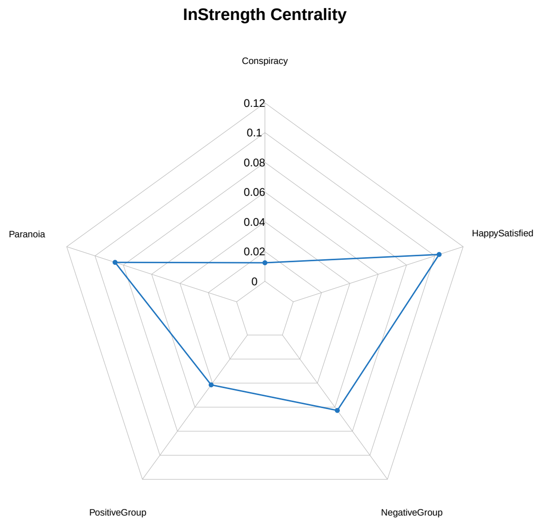


**Figure 3.5: Radar chart of the InStrength centrality (the sum of all incoming absolute edge weights to a node) of the variables in the temporal network.**

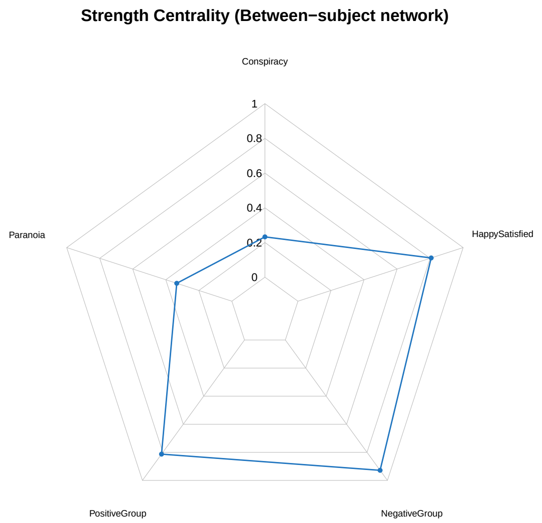


**Figure 3.6: Radar chart of the strength centrality (the sum of all absolute edge weights connected to a node), estimating the connectivity of the node in the between-subject network.**

from figure 3.2 and ignore the self reinforcement loops. That way we can scale up the connections between nodes to examine them in detail (Figure 3.3). At the top we see an expected relationship between the *positive group* and the *negative group*, with each inhibiting the other across time. Both also have their namesakes effect on *happiness and satisfaction*. Another large effect is *conspiracy* driving *paranoia*, which in turn results in lower *happiness and satisfaction*. This is evidence for conspiracy being a root cause of negative mental well-being, rather than an effect. We do not see any major effect of mental well-being on conspiracy, there is a connection between the *positive group* and both *conspiracy* (excitatory) and *paranoia* (inhibitory), however these effects are already scaled up and therefore of very low statistical significance.

**Centrality Analysis**

That being said, *conspiracy* was relatively inert across both networks, with minimal interaction between it and mental well-being. This can be seen clearly from the radar charts in figures 3.4, 3.5, and 3.6. These radar charts visualise the centrality of the nodes within the networks. That is an estimation of the importance of a node in the network.

As the temporal network (Fig. 3.2) is directional there are two measures of centrality for each node therein. The out-strength centrality, calculated from the sum of all outgoing absolute edge weights from a node (Figure 3.4), and the in-strength centrality, calculated from the sum of all incoming absolute edge weights to a node (Figure 3.5). Out-strength provides an estimate of how influential each node is in a network. That is how large an effect fluctuations in that node will have on other nodes in the network. In-strength estimates how easily influenced a node is by fluctuations in other nodes.

Additionally, from the between-subjects network we can generate a radar chart of strength centrality, calculated from the sum of all absolute edge weights connected to a node. This gives a more general estimate of how important each node is in the network.

We see that the *negative group* and *positive group* score highly in strength and out-strength, showing that these sets of emotions are the driving forces of mental well-being. *Happiness and satisfaction* and *paranoia* only score highly on in-strength centrality, suggesting these states are effects of mental well-being. In comparison, in all three charts *conspiracy* scores the lowest, indicating that relative to the other variables it is not reacting with mental well-being. We can see this from the networks in figures 3.1, 3.2, and 3.3, as its only major connections are a correlation with negative mental well-being, and a driving force on itself and to a lesser extent paranoia.

# 4 Conclusions

**Conspiracy and Mental Well-Being**

In this project I set out to investigate the link between conspiracy and mental well-being using network analysis. To that end it appears that conspiracy has a minor but negative effect on mental well-being, while mental well-being has little impact on conspiracy. The networks reveal, as previous research has indicated, that conspiracy appears alongside negative mental well-being (van Prooijen & Douglas, 2018). Conspiracy results in an increase in paranoia, which in turn reduces happiness and satisfaction over time. Conspiracy also propagates itself across time, with little influence from mental well-being, which may indicate the existence of outside sources either instigating or aiding to propagate conspiracy.

**Potential Issues**

While network analysis is a powerful tool, it has its limitations. As we have seen here, it cannot capture elements potentially outside the network. While strong self reinforcement loops in the network may indicate the presence of missing influential nodes, they cannot be distinguished from simply self reinforcing phenomena. This leads to ambiguity in interpretation, as we saw here with conspiracy.

Multi-level vector auto-regression, with which the networks here were modelled, also requires very tidy data with a large number of data points evenly across all time points to be truly accurate. While steps can be taken to transform data into the appropriate multivariate time series required, there will always be an effect on accuracy. This is of note here as the Psycorona study did not always measure each variable every week, with some having multiple weeks between measurements. Not enough measurements for a variable can introduce

Nickell's bias; strong negative self-reinforcement loops in the temporal effects network unrepresentative of actual effects in the data (Nickell, 1981). As discussed in the methodology in section 2, steps were taken to mitigate this by replacing missing values with the mean of that variable up to that point in time. Nevertheless, the effects of these approaches to missing data on the accuracy of the networks is still unclear and requires further assessment in general (Jordan, Winer, & Salem, 2020b).

**Further Research**

That being said, I believe this project has shown the potential of this type of analysis on conspiracy and mental well being. Going forward, another more focused longitudinal study would help improve these networks. Psychopathology often uses diary studies, which take measurements of the relevant variables daily. This could greatly improve these kind of networks as the fluctuations in mental states may be too quick to capture on the week to week timescale that was used here.

While this could give a clearer picture on conspiracy's effect on mental well-being, finding the root causes of conspiracy may require a different approach. There is a growing body of social psychology literature looking into the possible political (Lewandowsky, Oberauer, & Gignac, 2013; Miller, Saunders, & Farhart, 2016) and social (Van Prooijen & Jostmann, 2013; van Prooijen & Douglas, 2018) origins of conspiracy. The results here suggest that this, rather than a psychopathology approach, could be necessary to find the roots of conspiracy. A crucial step if we wish to mitigate its effects on our mental well-being.

Network analysis may still have a role to play however. Once these root causes, such as potentially time spent engaging with social media, political material, various news outlets, or other individuals with high self reported conspiracy, have been identified, these variables and their interaction with conspiracy could be visualised in a network to gain a clearer picture of what is happening (Bale, 2007; van Prooijen & Douglas, 2018; Oliver & Wood, 2014).

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# A Demographics

Information on the gender distribution is contained in figure A.1. The spread of ages and educational background can be found in figures A.2 and A.3. A heat map showing the country each respondent self reported living in is included in fig A.4. The demographics of the sample aligned quite well with the overall demographics of the full Psycorona study itself (*PsyCorona: Data Visualization.*, 2021).

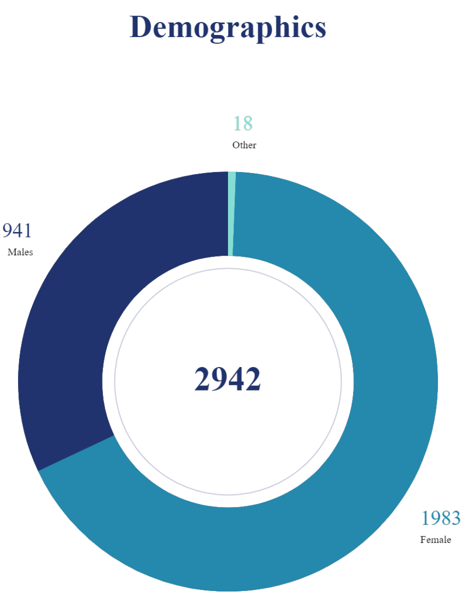


**Figure A.1: Gender distribution of subjects used in analysis, based on self reporting.**

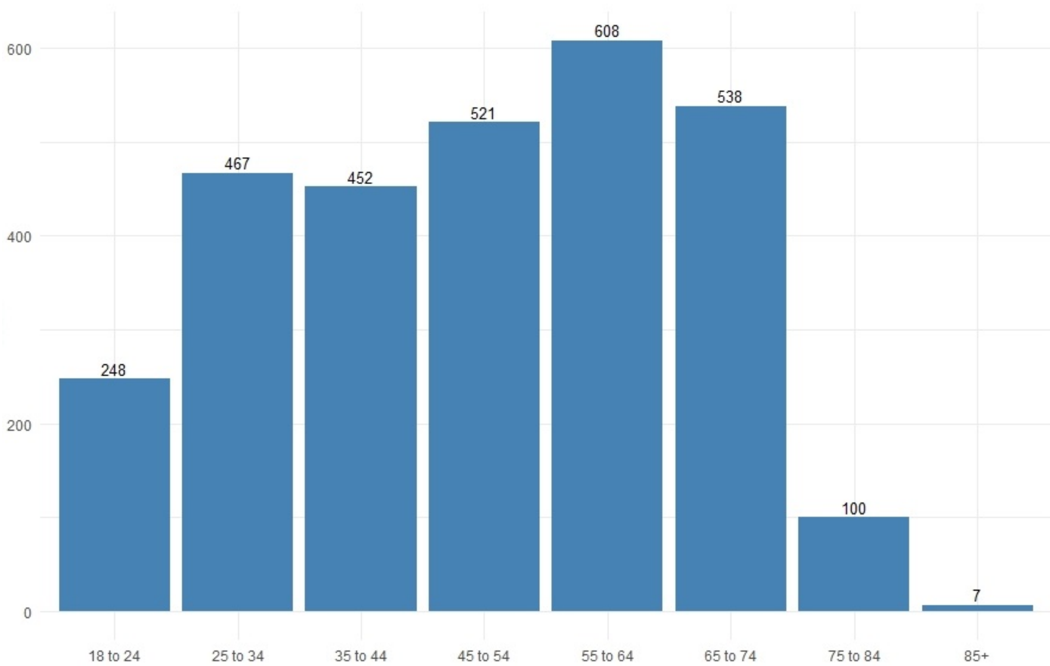


**Figure A.2: Histogram of respondents by age range.**

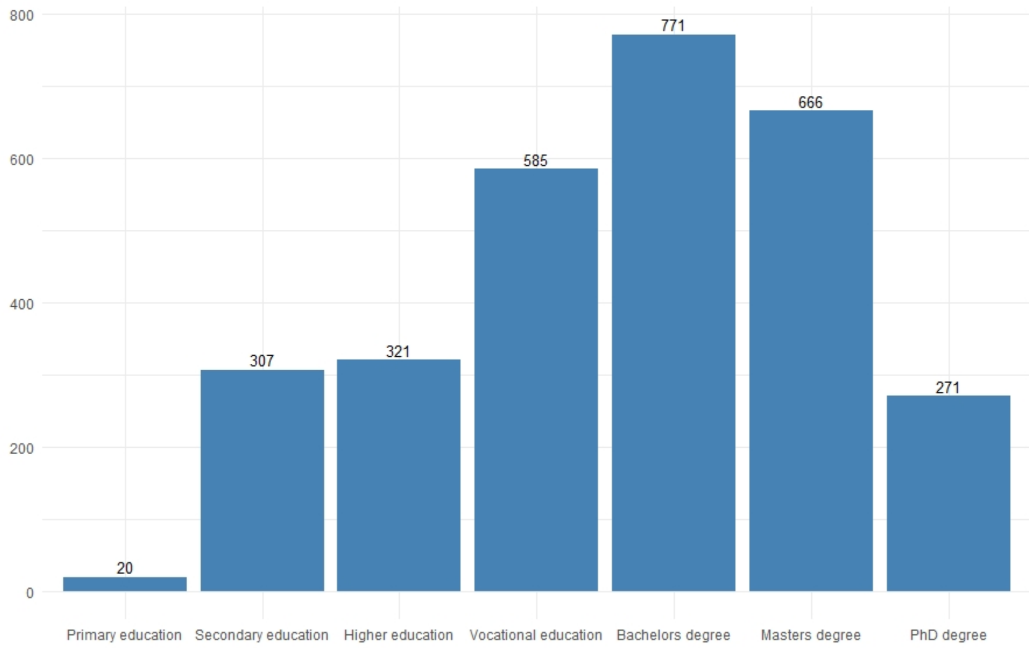


**Figure A.3: Histogram of respondents by education level.**

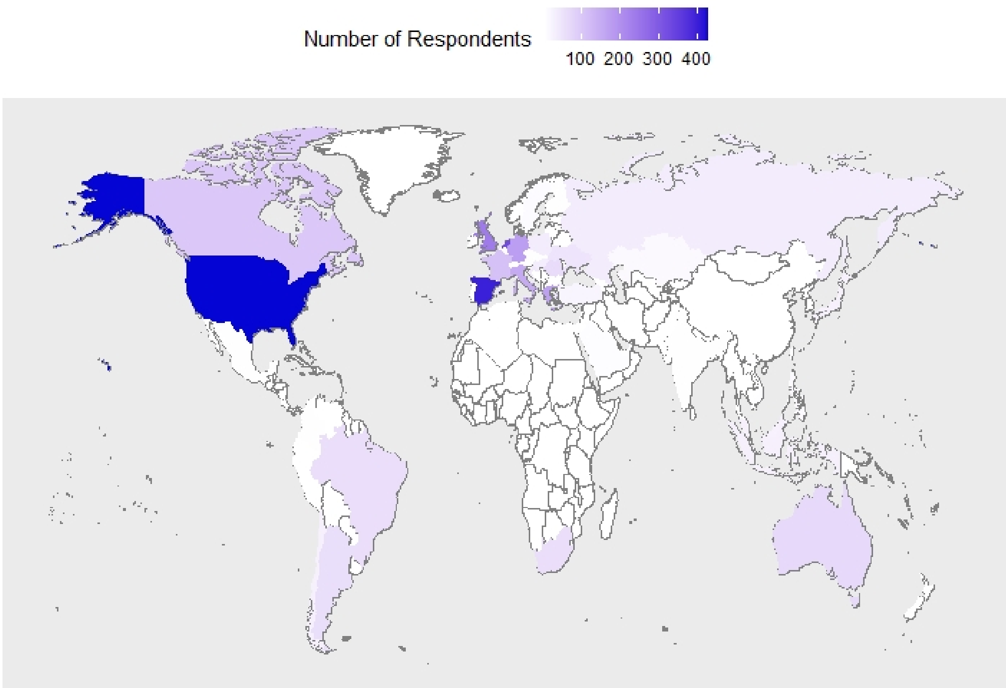


**Figure A.4: Heat map of countries of respondents. Darker blue indicates more respondents self-reported living in said country. The top five countries by number of respondents were: USA (427), Spain (397), Netherlands (325), UK (237), and Germany (174).**