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The Effect of Mental Illness on Compensation for IT Developers

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Abstract

Nearly 20% of US adults suffer from some form of mental illness. The indirect effects of the COVID-19 virus have increased this number significantly. The effect of mental illness on ability to work effectively and efficiently has been studied extensively and the consensus is that mental illness has a stigma associated with it that reduces employment opportunities for those so afflicted. Our study reviews this assumption by analyzing compensation for information technology developers who self-identify as having one of many mental illnesses. A large sample set from Stack Overflow was used to compare compensation levels based on this self-identification of one or more mental illnesses to determine if there was any significant impact. Our results found that overall mental illness does reduce compensation levels for information technology developers but less than many other variables. Other demographic factors, including a lower level of education, female gender, and younger age, are more significant factors for lower developer compensation. There is also a small effect based on ethnicity.

Keywords: Mental Illness, Compensation, Gender, Education

1. INTRODUCTION

The COVID-19 pandemic has caused a rise in the number of mental illness cases worldwide (Xie, Xu, & Al-Aly, 2022). Mental illness encompasses a wide range of conditions including depression, anxiety disorders, schizophrenia, eating disorders and addictive behaviors. It can affect a person's mood, thinking and behavior (MayoClinic, 2022a). Mental health "includes our emotional, psychological, and social well-being. It affects how we think, feel, and act. It also helps determine how we handle stress, relate to others, and make healthy choices" (Center for Disease Control, 2022). While the terms mental illness and mental health are commonly used interchangeably, they are not the same. A person may have a diagnosed mental illness, but at times be in good mental health. On the other hand, a person may be experiencing poor mental health without a diagnosed mental illness.

In 2019, just prior to the COVID-19 pandemic, 19.86% of U.S. adults experienced some form of mental illness (Mental Health America, 2022). SingleCare (2022) conducted a national survey on mental health and coronavirus and found that 59% of people in the US stated that their mental health was impacted by the COVID-19 pandemic. In addition, according to a study by the World Health Organization (2022), the COVID-19 pandemic has resulted in a 25% increase in the prevalence of anxiety and depression worldwide.

Prior research has shown that social disadvantage, especially lack of material possessions, lower income, and financial difficulties, are often associated with mental illnesses (Reading, 2000, Lewis, 1998, and Welch, 1998). In addition, women have been found to be diagnosed with a mental illness more often than men (Mayo Clinic, 2022b). During the COVID-19 pandemic, one in six women were found to have symptoms of post-traumatic stress – a rate like that of other significant disasters (Lindau, Makelarski, Boyd, Doyle, Haider, Kumar, Lee, Pinkerton, Tobin, Vu, Wroblewski, & Lengyel, 2021).

During the pandemic, many companies were required to conduct business virtually and could not operate at full capacity, which necessitated reducing their workforce (US Bureau of Labor Statistics, 2022). While the technology industry was not immune to this issue, it was in a better position overall (Hylton, Ice, & Krutsch, 2022). The pandemic created additional responsibilities and added layers of complexity to the IT professional's workload. This added stress and pressure to many IT professionals in the field (Thompson, 2022). Prior to the pandemic, fifty-one percent of IT professionals indicated that they were already diagnosed with a mental illness (OSMI, 2016). As new positions and roles are created to meet the demands post-pandemic, it will be important to understand how mental illness impacts the IT industry.

This paper looks to answer the following research questions:

- What impact does mental illness have on compensation (i.e., income) in the IT industry?
- What is the impact of gender in the relationship between mental illness and compensation?
- What is the impact of education in the relationship between mental illness and compensation?
- Are there any variables that have more of an impact on compensation than mental illness?

The next section will provide a literature review om the effects of mental illness on, compensation, education, and gender. This is followed by the methodology, results, and conclusions.

2. LITERATURE REVIEW

Mental Illness & Compensation

A study by Kose (2020) found a causal and positive relationship between household income level and the mental health of individuals in Turkey. They also reported that Turkish females had lower mental health than Turkish males.

Gresenz, Sturm, and Tang (2001) studied the relationship between income inequality and mental disorder. They found that mental health worsens, and the probability of depression and anxiety increases as the income of the family decreases. Wildman (2003) found that one's financial status is a determinant of mental health, and one's income creates inequalities in health. Moreover, Strohschein (2005) studied school age children between the ages of four and fourteen. She found that low household income results in greater depression, with improvements or increases in household income resulting in reduced mental health issues in children.

In particular, the COVID-19 pandemic lockdown was found to affect mental health more in low-income households (Pieh, Budimir, and Probst, 2020). In Pieh, Budimir, and Pobst's study they looked at residents of Austria during the first four weeks of lockdown. They determined that stress levels were higher for low-income households, adults under 35 years of age, and women. Pieh et al. (2021) also studied residents in the United Kingdom. They found that individuals from low-income households, younger than 35 years of age, and women experienced greater mental health issue. Li et al. (2020) also found similar results. They found that people who had larger income losses were at higher risk for mental health issues and required more psychological care. Historically, socially disadvantaged groups, such as those with low income, have shown more psychiatric illnesses or conditions than socially advantaged groups (Purtle, 2020).

However, another study by Araya et al. (2003) looked at adults living in Chile and found there was a strong, inverse, and independent association between education and common mental illnesses. But income was not associated with the prevalence of common mental illnesses, after adjusting for other socioeconomic variables.

Mental Illness & Gender

Prior research studies have found that women tend to experience higher instances of mental illness (Chochrane, 1981, Hankin, 2001, Macintyre 1996). The Substance Abuse and Mental Health Services Administration conducted the 2020 National Survey on Drug Use and Health and found that mental illness of any kind was higher among females (25.8%) than males (15.8%) (National Institute of Mental Health, 2022).

Seedat et al. (2009) found that gender differences in mental illness are consistently observed in various countries from different regions of the world, but they found that gender differences decline when men and women have more equal roles in the society.

Existing mental illness was appeared to be exacerbated during the pandemic. Many individuals were hospitalized for long periods of time without the ability to see their families. Prior to the pandemic, Paulo da Silva Ramos, et al. (2022) surveyed hospitalized patients using the Hospital Anxiety and Depression Scale and the Beck's Anxiety Inventory. Results showed that women had a higher level of anxiety than men. However, there was no difference in the level of depression. As previously stated, women were found to be affected more than men by the pandemic in Austria, with higher stress levels recorded for women during the first four weeks of lockdown (Pieh, Budimir, and Probst, 2020). This was also found to be true in the United Kingdom (Pieh et al., 2021).

Prowse et al. (2021) examined the COVID-19 pandemic's effect on the stress and mental health of university students in Canada. They found female students to more negatively affected than male students in terms of academics, stress, mental health, and isolation.

Due to increasing cases of Covid-19 cases many states called for lockdowns. Adams-Prassl, et al. (2022) studied the effects of the lockdown measures on mental health. They determined that the stay-at-home orders led to an overall decrease in mental health. They found a 61% increase in the gender gap in mental health with the negative impact of the lockdown impacting women more. The authors also found a positive association with income and a university degree with mental health.

Mental Illness & Education

Previous research has shown a definitive relationship between educational outcomes and mental illness. The research suggests two main reasons for this relationship, social causation, and social selection. Social causation research suggests that the relationship is a causal one and education affects mental health (Kessler et al. 1995; Lantz et al. 2005; Mirowsky and Ross 2003; Ritsher et al. 2001; Schieman and Plickert, 2008). Whereas the research on selection suggests that preexisting mental health conditions inhibit an individuals' ability to obtain a high level of education.

The causal relationship subscribes those higher levels of education enhance people's skills, afford important structural advantages, and empower better coping mechanisms, which results in better mental health.

The social selection theory prescribes that the link between education and mental illness may stem from preexisting conditions. Those experiencing these mental health problems are more likely to experience school difficulties, including more absenteeism, higher rates of suspension and expulsion, lower grades and test scores, and greater high school dropout propensity (Bernstein, 1997, Diperna, 2002, Gutman, 2003, & Reid, 2004). Research suggests that functional impairments and/or the stigma and social exclusion that go along with mental health illness are often the cause (McLeod, Uemura, and Rohrman 2012; Needham, Crosnoe, and Muller 2004).

Alternatively, a British study, by Lewis et al. (1993) revealed an interaction between social class and sex, and no independent association with educational achievement.

3. METHODOLOGY

To study the effects of mental illness on software developers' data from the 2021 Stack Overflow survey was used. Stack Overflow's annual Developer Survey is the largest and most comprehensive survey of people who code around the world. Each year, their survey questions cover a wide range of areas, from developers' favorite technologies to their job preferences. According to their website:

> "For almost a decade, Stack Overflow's annual Developer Survey held the honor of being the largest survey of people who code around the world. This year (2020), rather than aiming to be the biggest, we set out to make our survey more representative of the diversity of programmers worldwide. That said, the survey is still big. This year's survey was taken by nearly 65,000 people." (Stack Overflow, 2020)

The use of Stack Overflow is well established as a source for peer-reviewed journals including Barua, Thomas, and Hassan (2014), Asaduzzaman, Mashiyat, Roy, and Schneider (2013), and Treude and Robillard (2016). The Stack Overflow dataset consists of dozens of demographics, descriptive, and opinion questions about the state of programming today. The results were analyzed using IBM SPSS 27. It is important to note that the responses regarding mental health were self-reported and could also include responses that were self-diagnosed.

This survey was used as the starting point for our analysis. Over 88,420 survey responses were received, but the survey included data on respondents who were just hobbyists or non-professional users. In addition, this was an international survey and to eliminate international variations in salary this research just focused on US only developers. Finally, there were anomalies in compensation with unrealistically large compensation levels. Those reporting yearly salaries over $500,000 were excluded. To summarize, the initial data was filtered to only include the surveys from individuals who lived in the United States, identified as a developer by profession, and whose converted compensation was less than $500,000. All responses that were missing data or the responses were rather not say were removed from the dataset. After filtering, the dataset was still quite large with just over 7,500 responses.

SPSS 27 was used to perform a variety of statistical analyses to determine the impact of mental health and information technology compensation. The working hypothesis was that if mental health does affect employment opportunities, would this be manifested in compensation levels. The goal was also to compare the magnitude of the effect of mental health issues on compensation as compared to other demographic variables.

4. RESULTS

The survey asked the following question to ascertain the respondents' mental health:

Which of the following describe you, if any? Please check all that apply.

- I have a concentration and/or memory disorder (e.g., ADHD)
- I have a mood or emotional disorder (e.g., depression, bipolar disorder)
- I have an anxiety disorder
- I have autism / an autism spectrum disorder (e.g., Asperger's)
- None of the above
- In your own words

The results of this survey question are shown in Appendix A and Figure 1. Appendix A shows the count and average salary of all the different combinations of responses. As respondents can check more than one disorder there are many different combinations. Figure 1 on the other hand, shows the respondents' results for each of the response options. Given that respondents can check more than one disorder, the sum of the columns is larger than the total number of respondents. Approximately, 67% of the respondents indicated that they had no mental disorders, and 33% indicated that they had some type of mental disorder.

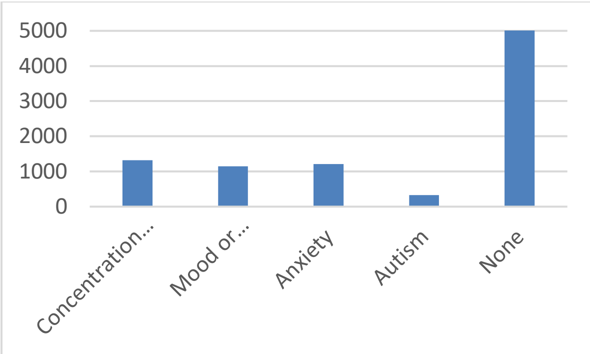

Figure 1: Count of Mental Disorder

Figure 2 shows the average salary of the respondents based on the mental disorder. The average salary of those indicating no mental disorder had the highest salary, just less than $140,000 while those who had an anxiety disorder had the lowest average salary of approximately $125,000.

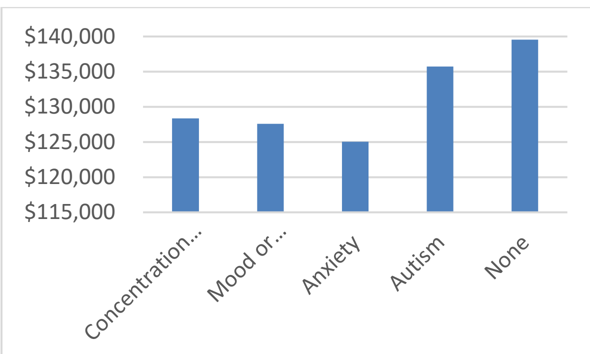

Figure 2: Average Salary by Mental Disorder

To further analyze if there was an overall difference between compensation levels for those who self-identified as having any mental illness versus those who did not, a simple binary variable was created. If the respondents indicated any type of mental disorder, the mental illness variable was a 1, otherwise it was set to zero. The results are shown in Tables 1 and 2. Overall, nearly 36% of the scrubbed dataset reported one or more mental illness. This is much higher than the estimated general population of 20%. As shown in table 2, there is more than a $10,000 difference between the compensation for those who reported a mental illness compared to those who did not. An ANOVA test was performed. This difference was significant a p< .001.

	Frequency	Percentage
No Mental Illness	5,011	66.5%
Mental Illness	2,520	33.5%
Total	7,531	

Table 1: Number of Respondents

	Mean	Std. Dev.
No Mental Illness	$139,547.99	$70,450
Mental Illness	$128,899.82	$65,125
Overall	$135,984.94	$68,893

Table 2: Average Salary by Mental Illness

To further investigate the factors that might affect the disparity in salary, each of the four important variables were added, that in past research have shown to affect job compensation: ethnicity, gender, age, and education level were separately analyzed.

Ethnicity was the first variable analyzed. Due to the more than 25 combinations of race in the dataset, the dataset was recoded to white and non-white so that a reasonable sample size was obtained. From the results in Table 3, the ethnicity factor used resulted in a small, but significant result for compensation. An ANOVA test was performed. The p value was less than 0.095, below the .10 threshold used in many social science studies. There was a $2000 increase in non-white versus white developers.

Ethnicity	Mean	N	Std Dev.
White	$135,276.90	5,863	$68,303
Non-White	$138,473.69	1,668	$70,895
Overall	$135,984.94	7,531	$68,894

Table 3: Average Salary by Ethnicity

Gender was the next variable that was independently analyzed. Those that self-reported and identified as other than solely male, or female were categorized into the other group. The results of the analysis are shown in tables 4 and 5. Women have significantly lower compensation. Their compensation was nearly $24,000 less than men and over $13,000 less than other gender. Women and Other also report much higher percentages of mental health issues (54% and 71%) versus men at 31%.

	Mean	N	Std Dev.
Male	$137,793.19	6,867	69,717
Female	$126,772.36	464	54,383
Other	$113,194.46	200	60,043

p < .001

Table 4: Average Salary by Gender

	No Mental Illness	Mental Illness	Total
Male	4,742	2,125	6,867
Female	212	252	464
Other	57	143	200

Table 5: Count of Gender & Mental Illness

The third independently reviewed variable was education level. The results are shown in Tables 6 and 7. In general, the higher the education level, the higher the compensation. An ANOVA test found this significant at p < .001. The results in Table 7 show that the level of education was affected by the having a mental disorder. An ANOVA test was performed, and it was determined that those having a higher education level had a lower incidence of mental illness. This was statistically significant at p < .001

Education	Mean	N	Std Dev.
Primary	$137,895.08	26	$81,273
High school	125,165.05	146	82,566
Some college	129,091.27	944	66,979
Associate	109,942.66	315	50,213
Bachelors	133,780.40	4472	67,586
Masters	151,218.19	1372	71,064
Doctoral /Advanced	156,296.00	256	76,581
Overall	135,984	7,531	68,893

Table 6: Average Salary by Education Level (Scaled)

Education	No Mental Illness	Mental Illness	Total
Primary	15 (58%)	11 (42%)	26
High school	80 (55%)	66 (45%)	146
Some college	507 (54%)	437 (46%)	944
Associate	181 (57%)	134 (43%)	315
Bachelors	3,009 (67%)	1,463 (33%)	4,472
Masters	1,041 (76%)	331 (24%)	1,372
Doctoral /Advanced	178 (70%)	78 (30%)	256
Overall	5,011 (67%)	2,520 (33%)	7,531

Table 7: Mental Illness & Education Level

The last factor analyzed was age. Age also had a significant impact on compensation level as shown in Tables 8 and 9. In general, older developers, at least up to age 54, had a higher compensation level than their younger counterparts. Also, younger developers from the appear to have higher levels of mental health issues as shown in Table 9. An ANOVA test was performed. Age was determined to be a significant variable affecting compensation at p < .001.

Age (years)	Mean	N	Std. Dev
18-24	$89,901.14	839	48382
25-34	130,281.01	3358	67099
35-44	153,857.37	2039	70,828
45-54	154,771.65	836	66,698
55-64	150,384.71	392	63,263
65 or older	136,370.15	67	60,518
Total	135,984.94	7,531	68,893

Table 8: Average Salary by Age

Age (years)	No Mental Illness	Mental Illness	Total
18-24	547 (65%)	292 (35%)	839
25-34	2,161 (64%)	1,197 (36%)	3,358
35-44	1,355 (66%)	684 (34%)	2,039
45-54	593 (71%)	243 (29%)	836
55-64	300 (77%)	92 (23%)	392
65 or older	55 (82%)	12 (18%)	67

Table 9: Age and Mental Health

With all these variables, different combinations will produce different results but to see an actual impact in a group, a major subset of the overall dataset was analyzed. The group consisted of only non-Women, Bachelor's degree, age 25-34, and white ethnicity. It was found that there was a $7000 difference in compensation for those without mental illness versus those with mental illness (Table 10). An ANOVA test was performed. This difference was significant at p < .046.

Mental Illness	Mean	N	Std. Dev.
No Mental Illness	$131,909.38	1,014	66,477
Mental Illness	124,982.51	543	62,625
Total	129,493.66	1,557	65,223

Table 10: Salary Differential of non-Women, Bachelor's degree, age 25-34, and white ethnicity with Mental Health

The final step was to utilize all the significant variables in a multiple regression analysis to determine the possible significance of each variable as well as determine any possible collinearity effects. The results of this analysis are shown in Appendix B.

Before discussing the specific regression coefficients and significance levels the collinearity analysis is first addressed. "Collinearity refers to the non-independence of predictor variables, usually in a regression-type analysis. It is a common feature of any descriptive ecological data set and can be a problem for parameter estimation because it inflates the variance of regression parameters and hence potentially leads to the wrong identification of relevant predictors in a statistical model." (Dorman, et al., 2013, p. 27) In other words, collinearity is bad and can result in improper conclusions because the variables may be non-independent and thus inaccurately predict the dependent variable.

There are multiple methods to determine collinearity and the two main methods are included in the SPSS output tables. The three key indices are Tolerance, VIF (Variance Inflation Factor) and Condition Index. The negative thresholds for these factors are less than .1 for tolerance, greater than 10 for VIF and greater than 30 for Condition index (Dorman, et al., 2013). The results show for all the variables the VIF's are below 1.1, all tolerances greater than .9 and no dimension condition indices above 16. Therefore, we can conclude that there are no collinearity issues with the variables, and all are independent of each other.

Now that the collinearity was checked, the next step was to analyze the results. It is worth noting that all variables were scaled or were dichotomous to allow for regression analysis. For gender, two dummy variables were added to determine the effect of women versus men and other versus men.

All variables included in the regression analysis were statistically significant at $p < .002$ except for other gender. Other gender did not have an impact on compensation with a p value of .20.

Evaluating all the variables, the statistical results show:

- Age is a significant factor in determining developer compensation. The older you are up to a point, the higher your compensation.
- Gender is a significant variable but only for women, not other. Women have lower compensation than men.
- Education level is a significant factor in determining developer compensation. The more education, the higher the compensation.
- Mental health is a significant factor by itself in determining developer compensation.
- Finally, ethnicity is also significant factor in determining developer compensation.

But these variables do not equally affect compensation. A review of the standardized coefficients reveals that the most important variable is age at .22. The next most important variable is Education level at .095. The third most important variable is gender but only for women at -.075. Ethnicity also has a slightly higher impact at .036, higher than mental health which is the lowest at -.035.

This data also supports the need for transparency in salaries to help ensure pay equity across all dimensions including ethnicities. Practitioners should work towards correcting their salary disparities between ethnicities.

5. CONCLUSIONS AND LIMTIATIONS

The data suggests that overall mental health issues are a significant factor in determining IT developer compensation, but not as high as other variables. Rather age and education level appear to be more important factors in contributing towards lower compensation. In addition, female gender, and ethnicity also play stronger roles. So overall, independently, mental health issues do reduce compensation, but have less effect than many other variables.

It should be noted that the data was from respondents who self-diagnosed their mental health. Additional research should be performed with medical data to further support these results.

Additionally, this study looked at variables available in the survey. It did not look at other potential mediating variables that may affect mental health. Researchers will want to conduct further research to determine if there are any other significant factors that play a role in mental health and compensation.

This data further supports the need for gender parity in compensation. Practitioners should look for ways of correcting salary disparities between genders.

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Appendices

MentalHealth	Mean	N
▪ concentration and/or memory disorder (e.g. ADHD)	$130,641	628
▪ concentration and/or memory disorder (e.g. ADHD); ▪ mood or emotional disorder (e.g. depression, bipolar disorder)	139,442	139
▪ concentration and/or memory disorder (e.g. ADHD); ▪ mood or emotional disorder (e.g. depression, bipolar disorder); ▪ anxiety disorder	122,269	250
▪ concentration and/or memory disorder (e.g. ADHD); ▪ mood or emotional disorder (e.g. depression, bipolar, disorder) ▪ anxiety disorder; ▪ Autism / an autism spectrum disorder (e.g. Asperger's)	132,636	55
▪ concentration and/or memory disorder (e.g. ADHD); ▪ mood or emotional disorder (e.g. depression, bipolar disorder); ▪ anxiety disorder; ▪ Autism / an autism spectrum disorder (e.g. Asperger's); ▪ Or, in your own words:	80,000	1
▪ concentration and/or memory disorder (e.g. ADHD); ▪ mood or emotional disorder (e.g. depression, bipolar disorder); ▪ anxiety disorder; ▪ Or in your own words:	98,800	6
▪ concentration and/or memory disorder (e.g. ADHD); ▪ mood or emotional disorder (e.g. depression, bipolar disorder); ▪ Autism / an autism spectrum disorder (e.g. Asperger's)	137,263	19
▪ concentration and/or memory disorder (e.g. ADHD); ▪ mood or emotional disorder (e.g. depression, bipolar disorder); ▪ Or, in your own words:	140,333	6
▪ concentration and/or memory disorder (e.g. ADHD); ▪ anxiety disorder	115,612	129
▪ concentration and/or memory disorder (e.g. ADHD); ▪ anxiety disorder; ▪ Autism / an autism spectrum disorder (e.g. Asperger's)	125,461	21
▪ concentration and/or memory disorder (e.g. ADHD); ▪ anxiety disorder; ▪ Or, in your own words:	107,500	2
▪ concentration and/or memory disorder (e.g. ADHD); ▪ Autism / an autism spectrum disorder (e.g. Asperger's)	132,129	54
▪ concentration and/or memory disorder (e.g. ADHD); ▪ Or, in your own words:	117,133	14

▪ mood or emotional disorder (e.g. depression, bipolar disorder)	126,893	317
▪ mood or emotional disorder (e.g. depression, bipolar disorder); ▪ anxiety disorder	124,327	301
▪ mood or emotional disorder (e.g. depression, bipolar disorder); ▪ anxiety disorder; ▪ Autism / an autism spectrum disorder (e.g. Asperger's)	113,117	25
▪ mood or emotional disorder (e.g. depression, bipolar disorder); ▪ anxiety disorder; ▪ Or, in your own words:	124,850	2
▪ mood or emotional disorder (e.g. depression, bipolar disorder); ▪ Autism / an autism spectrum disorder (e.g. Asperger's)	165,600	18
▪ mood or emotional disorder (e.g. depression, bipolar disorder); ▪ Or, in your own words:	159,625	8
▪ anxiety disorder	131,383	379
▪ anxiety disorder; ▪ Autism / an autism spectrum disorder (e.g. Asperger's)	130,633	24
▪ Anxiety disorder; ▪ Autism / an autism spectrum disorder (e.g. Asperger's); ▪ Or, in your own words:	93,000	2
▪ anxiety disorder; ▪ Or, in your own words:	101,400	10
▪ Autism / an autism spectrum disorder (e.g. Asperger's)	142,353	109
▪ Autism / an autism spectrum disorder (e.g. Asperger's); ▪ Or, in your own words:	250,000	1
None of the above	139,548	5,011

Appendix B Regression and Collinearity Results

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standard. Coeff. Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	64029.663	4812.012		13.306	.000		
	Mental HealthN	-5143.495	1656.803	-.035	-3.104	.002	.960	1.042
	Ethnicity	5917.824	1861.583	.036	3.179	.001	.982	1.018
	EducN	6306.749	746.751	.095	8.446	.000	.976	1.025
	Woman	-21409.143	3217.936	-.075	-6.653	.000	.980	1.020
	OtherN	-13370.434	10438.117	-.014	-1.281	.200	.995	1.005
	AgeN	14390.041	734.509	.220	19.591	.000	.981	1.019

a. Dependent Variable: Compensation,

Collinearity Diagnostics[a]

Model	Dim.	Eigen Value	Condition Index	Variance Proportions (Constant)	Mental HealthN	Ethnic,	EducN	Woman	OtherN	AgeN
1	1	4.245	1.000	.00	.02	.01	.00	.01	.00	.01
	2	1.002	2.059	.00	.00	.00	.00	.05	.93	.00
	3	.925	2.142	.00	.02	.00	.00	.87	.04	.00
	4	.608	2.643	.00	.90	.00	.00	.07	.02	.01
	5	.138	5.547	.00	.00	.26	.00	.01	.00	.64
	6	.065	8.095	.03	.00	.59	.28	.00	.00	.24
	7	.018	15.573	.97	.05	.14	.71	.00	.00	.11

a. Dependent Variable: Compensation