The Prediction of Personality on Psychology Student's Technology Acceptance Regarding Future Careers

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Abstract

Understanding the extent to which psychology students embrace technology is essential for their future careers as psychologists and can benefit both academic research and psychological education. There can be diversity among psychology student's acceptance of technology regarding their future careers. In this study, personality traits are considered the independent variables, and the overall acceptance of technology regarding students' future careers is taken as the dependent variable. Therefore, this thesis utilises the Technology Acceptance Model (TAM) and the Big Five Inventory-2-XS (BFI-2-XS) to measure the prediction of personality traits for this diversity. All in all, a cross-sectional survey study using convenience sampling was employed, resulting in a sample of 52 participants. Even though no statistically significant relationship was found, weak correlations were discovered, representing Openness to Experience and Conscientiousness having a negative relationship, Extraversion having a positive relationship, and Agreeableness and Neuroticism having both positive and negative relationships with indicators of technology acceptance concerning future jobs of psychology students. Overall, this study contributes to research since it provides insight into the unique relationship between personality traits and overall technology acceptance about the future careers of psychology students.

Keywords: The Big Five Personality Traits, Technology Acceptance Regarding Future Careers, Psychology Students, TAM, BFI-2-XS

The Prediction of Personality on Psychology Student's Technology Acceptance Regarding Future Careers

By considering the current era—the Fourth Industrial Revolution—as one of innovation, where technological progress continuously creates changes in the workplace, work opportunities, and work practices, individuals can adapt accordingly and acquire new skills related to this new technology (Skrbiš & Laughland-Booÿ, 2019). For example, employees may need to know how to work with artificial intelligence (AI), which can give them a competitive edge in the labour market (Jarrahi, 2018; Skrbiš & Laughland-Booÿ, 2019). Moreover, according to Skrbiš and Laughland-Booÿ (2019), "Alongside technological progress, history has always seen the disappearance of some jobs and the emergence of others. What is new is that advancements are now occurring exponentially and simultaneously" (p. 191). Thus, the high rate of advancements being made highlights the significant role of technology in defining future careers.

This fast technological change can be seen in the field of psychology too. With the rising use of technology in psychologists' jobs, the ability to adapt to this technology is becoming a must (De Vos et al., 2021). Consequently, understanding the extent psychology students are accepting of this technology, is crucial for their future careers as psychologists. That said, not everyone embraces technology in the same way. Whilst some approach the evolving role of technology in the workplace with confidence, others show concern about their job stability (Skrbiš & Laughland-Booÿ, 2019). For example, the use of AI can elicit worry about ethics and feeling replaceable, yet it can offer hope for the future of healthcare and education as well (Fast & Horvitz, 2017).

Furthermore, according to Behrenbruch et al. (2013), "there is a great diversity in reactions to new technology in terms of acceptance" (p. 306). It is evident that there are various factors that affect the acceptance of technology, such as computer self-efficacy, trust, expectations, etc. (Marangunić & Granić, 2014). Moreover, personality traits are one of the most prominently researched factors and are deemed to play a significant role in influencing this acceptance (Behrenbruch et al., 2013; Sindermann et al., 2020; Svendsen et al., 2013). Taking all of this together, investigating whether personality traits of psychology students are related to the overall acceptance of technology that these students have with regard to their future careers, can provide valuable insights for academic research as well as psychological education.

Overall Technology Acceptance

Psychologists use a large variety of technological devices in their practice, for instance by treating clients via videoconferencing or by utilising Virtual Reality (VR) devices (Cataldo et al., 2021; Martingano & Persky, 2021). Therefore, measuring overall technology acceptance and incorporating a broad definition of technology in the workplace can be useful (Scott & Timmerman, 1999). There are several definitions of technology (Carroll, 2017). The study of Li-Hua (2009, as cited in Carroll, 2017, p. 12) discusses the general definition of technology as "technology represents the combination of human understanding of natural laws and phenomena accumulated since ancient times to make things that fulfil our needs and desires or that perform certain functions, and that it has to create things that benefit human beings".

Although this definition captures the essence of technology, in this study, the definition of eHealth was employed in order to provide participants with a more straightforward understanding of this concept. The use of eHealth can benefit psychology students by serving as a useful tool within psychology, for example, by facilitating the administration of psychological interventions (Varela-Moreno et al., 2022). Specifically, technology with regard to eHealth is defined as "the use of technology to support health and well-being" (Jiménez-Zarco et al., 2020 & Oh et al., 2005, p. 2). Given the increasing importance of eHealth and recommendations to put it in curricula, it can be considered a fitting definition for technology in the workplace (Edirippulige et al., 2018).

The Technology Acceptance Model (TAM) is considered a dominant model for investigating the acceptance of this technology, using the constructs of Perceived Usefulness (PU) and Perceived Ease of Use (PEU) (Marangunić & Granić, 2014). PU entails the degree to which individuals believe that technology will improve their professional performance, while PEU refers to the expectation individuals have regarding the complexity of technology utilisation (Ruiz-Herrera et al., 2023). Together, these two constructs play a significant role in shaping individuals' attitudes about technology adoption and usage. In the longitudinal study of Aplin-Houtz et al. (2023), the TAM was administered to test the relationship between dark personality traits and technology acceptance in the workplace. They adapted the items to assess general technology acceptance rather than a particular type of technology, such as a specific app. Similarly, this study will employ the TAM questionnaire to measure the overall attitudes of Psychology students towards technology in relation to their future careers.

Personality Traits

Since the Big Five is the most widely employed and acknowledged model of personality traits today, this study will incorporate a Big Five personality inventory (Özbek et al., 2014; Rossberger, 2014, as cited in Ali, 2019). As the name suggests, the Big Five model consists of five personality traits, namely: Openness to Experience (O), Conscientiousness (C), Extraversion (E), Agreeableness (A), and Neuroticism (N) (Costa & McCrae, 1992, as cited in Shi et al., 2018). According to Matthews et al. (2003, as cited in Özbek et al., 2014, p. 543), Openness to Experience can be described as "the tendency to be imaginative, independent, and interested in variety vs. practical, conforming, and interested in routine" and Conscientiousness as "tendency to be organized, careful, and disciplined vs. disorganized, careless, and impulsive". Additionally, Costa and McCrae (1992, as cited in Shi et al., 2018,

p. 1) describe that Extraversion has a "focus on the interpersonal relationship: Extraversion reflects the tendency to be gregarious, enthusiastic, assertive, and to seek excitement". Lastly, Rossberger (2014, as cited in Ali, 2019, p. 39) defines Agreeableness as the "extent to which individuals value cooperation and social harmony, honesty, decency, and trustworthiness", and Neuroticism as the "extent to which individuals experience negative feelings and their tendency to emotionally overreact". Theoretically, all these factors encompass the essence of an individual's personality (Digman, 1990, As cited in McElroy et al., 2007).

Correspondingly, personality has been found to have an association with technology (Svendsen et al., 2013). Previous research has shown that the traits: "Openness to Experience, Conscientiousness, Extraversion, and Agreeableness", are associated with a positive relationship to Perceived Ease of Use (PEU), which is an indicator of technology acceptance (Özbek et al., 2014; Rivers, 2021; Svendsen et al., 2013). Additionally, Svendsen et al. (2013) state in their study that Extraversion has a positive relationship with Perceived Usefulness (PU), another indicator of technology acceptance. Lastly, it has been found that PU is negatively influenced by the trait Neuroticism (Devaraj et al., 2008; Terzis et al., 2012).

Current Study

To bring it all together, this study will address the research question: "Can personality traits predict the overall acceptance psychology students have for the role of technology in their future careers?" using a cross-sectional survey design. This study takes the perspective of a unidirectional relationship, aligning with the TAM model adopting this perspective too (Taherdoost, 2018). The results of this study can provide these students with an insight into the relationship between these variables, and consequently prepare them for the technological demands of their future profession as psychologists (Behrenbruch et al., 2013; De Vos et al., 2021; Skrbiš & Laughland-Booÿ, 2019). Moreover, this study can offer valuable insights for education and academic research as well (Granić & Marangunić, 2019). The following hypotheses were formulated to test the research question (see Figure 1):

Hypothesis 1 (H_1): Openness to Experience will positively predict the overall acceptance of technology in connection with future careers.

Hypothesis 2 (H_2): Conscientiousness will positively predict the overall acceptance of technology in connection with future careers.

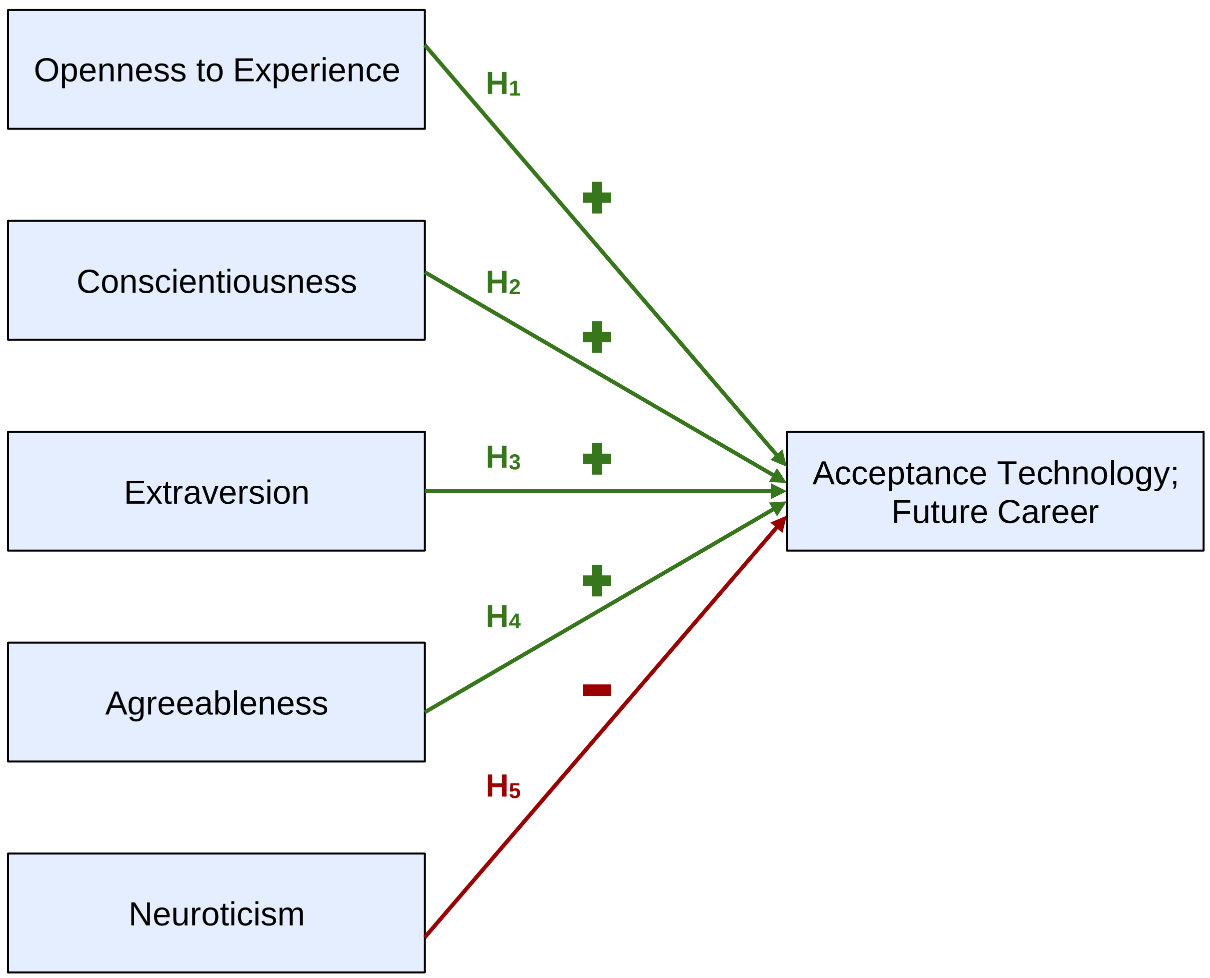
Hypothesis 3 (H_3): Extraversion will positively predict the overall acceptance of technology in connection with future careers.

Hypothesis 4 (H_4): Agreeableness will positively predict the overall acceptance of technology in connection with future careers.

Hypothesis 5 (H_5): Neuroticism will negatively predict the overall acceptance of technology in connection with future careers.

Figure 1

Conceptual Framework of the Variables and Their Expected Effects in This Study



Method

Study Design

To examine the prediction of the independent variables, the Big Five personality traits, on the dependent variable, the overall acceptance of technology regarding students' future careers, this study consists of a survey incorporating a quantitative, non-experimental, cross-sectional design. Notably, the survey employed in this study was part of a larger questionnaire, which contained additional questions about other psychological factors, such as affinity.

Procedure

To answer the research question, the target group comprises psychology students over the age of 16, studying at an academic university at the time of data collection. When recruiting these students, using convenience sampling, multiple distribution methods were employed. Students from the University of Twente could participate via the test subject pool “Sona Systems” in exchange for 0.25 credits (see Appendix A, Figure 2). Additionally, a poster and flyer with a QR code was designed, which participants could scan with their technological devices, to access the questionnaire (see Appendix B, Figures 3 and 4). The posters were hung in the room of the psychological association of the university, while the flyers were handed out to university students before their lecture. Lastly, the researchers directly invited individuals via social media, such as WhatsApp and Instagram.

The study was available for participants to complete from 08-04-2024 until 31-05-2024. As seen in Appendix C, the participants were shown information about the study and a clarification of technology within the framework of eHealth, provided earlier in the thesis, after using the QR code or link to access the study. Participants could navigate through the survey by clicking on the left or right arrow at the bottom, which would take them to the different pages. The second page of the survey consists of the Informed Consent form, where participants could choose to provide or withhold their consent. On the following page, the participants could fill in the demographic questions. Then, the first scale was presented, with questions that were part of another study. On the fifth page, questions regarding the personality traits from the BFI-2-XS questionnaire were displayed. Again, Page 6 involved questions from another questionnaire. On page 7, the participants were asked to complete the TAM questionnaire. Finally, the survey ended with a thank you message and a confirmation that the responses were recorded. If participants accessed the survey through Sona, their credits were granted approximately 3 days after they clicked on the link in Sona and started the survey. For this study, ethical approval was granted by the University of Twente.

Participants

Initially, this study focussed on cross-health related participants, but because the numbers were so low, only Psychology students were included. Additionally, it was stated that participants must be 16 years or older to be capable of giving consent and possess a sufficient level of the English language. In total, 18 participants were excluded, since the exclusion criteria are: "being younger than the age of 16, not giving informed consent, not being enrolled as a psychology student at an academic university, and not finishing both questionnaires". The final sample contained 52 participants, particularly 43 (82.7%) of them were female, six (11.5%) of them male, and three (5.8%) non-binary/third gender, aged 17 to 28 years old (M = 21.27, SD = 1.83). Participants spent an average of 18.86 minutes filling in the survey. Moreover, eight participants did not report their age, fortunately, this is not a primary variable of focus in this study. Additionally, keeping the data from these participants is deemed acceptable, since they did meet the inclusion criteria. Besides, 24 (46.2%) participants are Dutch, 18 (34.6%) German, and 10 (19.2%) have a different nationality. Notably, 22 (42.3%) participants want to work in the field of clinical psychology in the future. Moreover, 49 (94.2%) participants are studying at the University of Twente in the Netherlands and three (5.8%) at another university. Lastly, 22 (42.3%) participants are in their first or second year of their psychology bachelor's programme, while 30 (57.7%) are in more advanced years or already pursuing their master's degree.

Materials

The survey was created using "Qualtrics", which is a survey platform and tool to create and distribute surveys (Boas et al., 2018). The full survey is provided in Appendix C. To access and take part in this survey, the participants needed a digital device that could be connected to the internet, such as a mobile phone or laptop.

BFI-2-XS

For this study, the extra-short form of the Big Five Inventory–2 was utilised (BFI-2-XS). In this inventory, each personality trait domain is covered with three items. This short version was created by Soto and John (2017) and contained 15 items from the original Big Five Inventory–2 (BFI-2). Similar to what recent literature suggests, this study used a 1-5 Likert scale as the one used by the creators of the inventory (Soto & John, 2017; Rammstedt et al., 2023). The possible answers participants could give were: “Disagree strongly, Disagree a little, Neutral; no opinion, Agree a little, Agree strongly”. The reason for using this short version is that the questions for this study are part of a bigger survey, with additional questions from another study, and to account for assessment time and fatigue of participants this short version is an efficient choice (Soto & John, 2017). Even though this inventory doesn’t measure the specific facets of the traits, the short form effectively measures the Big Five personality trait domains themselves (Soto and John, 2017; Rammstedt et al., 2021). So, the subscales in this inventory are the five traits themselves. As seen in Appendix C, examples of the items are: “Openness to Experience: I am someone who is fascinated by art, music, or literature”, “Conscientiousness: I am someone who is reliable, can always be counted on”, “Extraversion: I am someone who is full of energy”, “Agreeableness: I am someone who is compassionate, has a soft heart”, “Neuroticism: I am someone who worries a lot”. Finally, there is a lot of research done with the BFI-2-XS being adapted and used in different countries, such as Morocco, Germany, Norway, and so on (Halama et al., 2020; Rammstedt et al., 2020; Føllesdal & Soto, 2022; Attar & Ouadi, 2023). The findings of each of these studies, suggesting that the inventory is valid and reliable, indicate that it can be implemented on a variety of students.

Technology Acceptance in Future Job

The TAM questionnaire is widely modified throughout research to accommodate diverse contexts and technologies (Granić & Marangunić, 2019). To test the objectives of this study, minor adaptations to the TAM questionnaire were applied as well. The items for adaptation were identified in the study of Cheah et al. (2022), where “the wordings in TAM questionnaire are unchanged except the ‘system’ is replaced” (p. 40). In order to fit this study, the same was done to integrate “technology in my future job”. The adapted TAM questionnaire employed, can be viewed in Appendix C. The questionnaire consists of 12 items measuring two indicators of technology acceptance, with the first six measuring the subscale PU, and the last six assessing the subscale PEU. Examples of items used in this current questionnaire are: “PU: Using technology will improve my job performance in the future” and “PEU: Learning to use technology in my future job will be easy for me”. The items can be rated on a 1-5 Likert scale, with the response options: “strongly agree, agree, no comment, disagree & strongly disagree” (Chen et al., 2008). Overall, the TAM model is considered to be valid, reliable, and suitable for university students (Fathema et al., 2014; Aplin-Houtz et al., 2023; Ruiz-Herrera et al., 2023).

Data Analysis

Importing the data as a “choice text” file from Qualtrics, was the first step in the data analysis process. Then, Rstudio with version R 4.1.1, was used. To start the analysis, the data was cleaned by employing the exclusion criteria specified in the participant section of this study. Additionally, the data was prepared for analysis by quantifying the responses of the participants, coding the Likert scale of the TAM to match that of the BFI-2-XS, reverse-coding pertinent items, sorting items with their corresponding subscales (for the BFI-2-XS questionnaire: “Openness to Experience: 5, 10R, 15”, “Conscientiousness: 3R, 8R, 13”, “Extraversion: 1R, 6, 11”, “Agreeableness: 2, 7R, 12”, and “Neuroticism; 4, 9, 14R” & for the adapted TAM model: “PU: 1-6”, and “PEU: 7-12”), and removing irrelevant data, for example data that is related to the other questionnaires in the survey was extracted (Soto & John, 2017; Cheah et al., 2022).

Then, the characteristics of the data were explored by examining values such as frequencies and means. Next, Cronbach's alpha was calculated to assess the reliability of the questionnaires, and a statistical method was employed to obtain correlations and carry out multiple linear regression analyses. Consequently, p-values, the direction of the effects of variables, the strength of the relationship, etc., were determined. Concerning the correlation analysis, six dummy variables were coded. Separate dummy variables were created for males, females, being German, and being Dutch. The purpose of this was to maintain the 52 observations in this study. Moreover, the dummy variable for Clinical Career Aspiration was created by coding participants' answers from the demographic questions about what type of psychologist they wanted to become in the future. This was done by including everything that has the word "clinical" in it, and rechecking if these answers indeed represented that the participants wanted a future career in the clinical field of psychology. Additionally, the final dummy variable, Study Year, was made by grouping first- and second-year bachelor participants together and comparing them with higher-year bachelor and master students, to examine the impact of being more mature and more experienced with technology and education.

Furthermore, the regression analyses proceeded, since the assumptions of normality, homoscedasticity, and linearity were reasonably met and regarded satisfactory with minor deviations but no severe violations (see Appendix D, Figures 5–8). The multiple linear regression analyses assessed the effects of each personality trait individually on PU and PEU. On top of that, a post-hoc power analysis was conducted, to determine if the eventual sample size was too small to witness an effect (Quach et al., 2022). Therefore, power was calculated using R. However, the effect size, termed Cohen's d, was computed using data from the regression analysis, in order to divide the estimate of the predictor variable by the residual standard error, as this accounts for variance. The residual has been included when calculating the effect size in previous research as well (Brysbaert & Stevens, 2018). Finally, utilising the data that was gained through this analysis, the hypotheses can be evaluated, and therefore the research question can be answered. The R-code for this analysis can be found in Appendix E.

Results

First and foremost, the reliability of the questionnaires is determined (see Table 1). Auspiciously, the Cronbach's alpha of the adapted TAM questionnaire is 0.94. However, the alphas of the subscales of the BFI-2-XS appear to have low to moderate reliability. An alpha of 0.7 or higher is widely perceived as a satisfactory level of reliability (Taber, 2017). Fortunately, another way to inspect the reliability of inventories and test the internal consistency of items is by looking at the correlations between the items of the subscales (Herman, 2014).

So, to address the low reliability of the personality subscales, each containing only three items, the inter-item correlations of these subscales were explored in order to gain a more accurate picture. Correlations between the items of Openness to Experience range from .22 to .25, for Conscientiousness it ranges from .20 to .46, items of Extraversion have a range of .05-.44, Agreeableness .17-.36, and Neuroticism .14-.55. Unfortunately, deleting items with a low correlation with the other items did not significantly improve the alpha as well. Notably, such an approach can limit exploration of the breadth of the construct being measured, considering it has only three items to begin with. Overall, while some subscales show more consistent relationships amongst their items, others exhibit more variability. In comparison the subscale PU has correlations ranging from .63 to .81 and the subscale PEU .61-.82, indicating strong correlations.

Table 1

Reliability of the Subscales

Subscale	***n***	***n* items**	**Cronbach's α**
Openness to Experience	52	3	0.49
Conscientiousness	52	3	0.62
Extraversion	52	3	0.55
Agreeableness	52	3	0.53
Neuroticism	52	3	0.66
PU	52	6	0.94
PEU	52	6	0.94

Note. PU = Perceived Usefulness of technology in future careers; PEU = Perceived Ease of Use of technology in future careers.

Next, Table 2 represents the descriptive statistics and Pearson correlations of the relevant variables in this study, while examining other factors such as gender, nationality, study year, and career aspirations as well. The means for the personality traits, PU, and PEU are all around three, which suggests neutrality in the participant's personality traits and technology acceptance. The standard deviations are less than one for these variables, indicating that there is not much variability in responses either. Some of these means are close to the number four, specifically the means of Openness to Experience, Agreeableness and PU. This implies a tendency of participants to lean slightly more towards agreement with these variables.

The correlations of Agreeableness and Neuroticism with PU seem to be positive but weak. Extraversion seems to have a weak positive correlation with both PU and PEU as well. For the rest, there seem to be only weak negative relationships between the traits with PU and PEU. As for the other factors, the variables about nationality, gender, and career aspiration do not seem to have a significant effect on PU or PEU. The variable Study Year, on the other hand, shows a significant negative moderate correlation with PU. Regarding the personality traits, being male demonstrates a moderate negative significant correlation with Agreeableness and being Dutch or German displays low negative and positive significant correlations with Neuroticism. Lastly, the variable Clinical Career Aspiration shows a moderate positive and significant correlation with Openness to Experience and Agreeableness.

Table 2

Descriptive Statistics and Correlation Table

Variable	*M*	*SD*	Min	Max	Median	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Openness to Experience	3.76	0.21	3.60	4.00	3.69	-												
2. Conscientiousness	3.29	0.85	2.58	4.23	3.06	.010	-											
3. Extraversion	3.06	0.58	2.69	3.73	2.77	.278*	.095	-										
4. Agreeableness	3.85	0.35	3.60	4.25	3.69	.426**	.090	-.149	-									
5. Neuroticism	3.38	0.50	2.90	3.90	3.33	-.013	-.322*	-.070	.071	-								
6. PU	3.88	0.12	3.75	4.04	3.84	-.068	-.226	.044	.104	.187	-							
7. PEU	3.40	0.10	3.27	3.54	3.39	-.129	-.043	.203	-.080	-.250	.542**	-						
8. Female (0 = Male + Other vs. 1 = Female)	0.83	0.38	0.00	1.00	1.00	-.102	-.123	-.088	.259	.116	.053	-.053	-					
9. Male (0 = Female + Other vs. 1 = Male)	0.12	0.32	0.00	1.00	0.00	-.020	.113	-.028	-.317*	-.150	-.090	-.064	-.789**	-				
10. Dutch (0 = German + Other vs. 1 = Dutch)	0.46	0.50	0.00	1.00	0.00	.124	.214	-.057	.267	-.286*	-.077	.191	-.086	.028	-			
11. German (0 = Dutch + Other vs. 1 = German)	0.35	0.48	0.00	1.00	0.00	-.059	-.119	-.024	.110	.276*	-.012	-.176	.119	-.136	-.674**	-		
12. Study Year (0 = Other vs. 1 = Bachelor 1 & 2)	0.42	0.50	0.00	1.00	0.00	.065	-.016	-.067	.053	-.242	-.361**	-.114	-.328*	.300*	.378**	-.296*	-	
13. Clinical Career Aspiration (0 = Other vs. 1 = Clinical)	0.42	0.50	0.00	1.00	0.00	.366**	-.046	.233	.321*	.143	-.097	-.182	.083	-.187	.144	-.050	.133	-

Note. PU = Perceived Usefulness of technology in future careers; PEU = Perceived Ease of Use of technology in future careers. $n = 52$, $df = 50$.

*$p < .05$.

**$p < .01$.

To test the hypotheses of this study, multiple linear regression analyses were conducted (see Table 3). These regression analyses were done for both PU and PEU separately, since these dependent variables relate differently to the personality traits, as follows from the correlation analysis. Yet, the regression for both dependent variables taken together was tested as well, and it did not reveal any significance. The results suggest that there is no significant prediction between the personality traits with both PU and PEU. In addition, the confidence intervals also indicate that there could be no effect, as they include zero, which represents the Null hypothesis (Hespanhol et al., 2019). As shown in Table 3, these confidence intervals are considerably wide, which indicates uncertainty in the estimate as well. Furthermore, the estimates found in this study appear to be quite low while their standard errors (SEs) are notably high. This indicates significant variability in the estimate, rendering it uncertain (Abadie et al., 2020).

Table 3

Regression Table: Effects on PU and PEU

Variable	**Est.**	***SE***	**95% CI**		***p***
			LL	***UL***	
PU					
Openness to Experience	-0.08	0.16	-0.40	0.25	.634
Conscientiousness	-0.22	0.13	-0.49	0.05	.107
Extraversion	0.05	0.14	-0.24	0.33	.755

Agreeableness	0.11	0.15	-0.19	0.42	.464
Neuroticism	0.17	0.13	-0.08	0.43	.183
PEU					
Openness to Experience	-0.15	0.16	-0.48	0.18	.363
Conscientiousness	-0.04	0.14	-0.33	0.24	.763
Extraversion	0.21	0.14	-0.08	0.50	.149
Agreeableness	-0.09	0.15	-0.40	0.22	.574
Neuroticism	-0.23	0.13	-0.49	0.02	.074

Note. This table demonstrates the effects of the Big Five personality traits on Perceived Usefulness (PU) and Perceived Ease of Use (PEU) of technology in future careers. n = 52, df = 50. CI = Confidence Interval; *LL* = Lower Limit; *UL* = Upper Limit.

Finally, the power and the effect size, represented by Cohen’s d, of the post-hoc power analysis can be seen in Table 4. Notably, power in a study can be reduced by a small sample size and low effect size (Serdar et al., 2021). Additionally, effect sizes indicate the variance and strength of associations (Kang, 2021). According to Kang (2021), conventional effect sizes are “values of 0.2, 0.5, and 0.8 for small, medium, and large effect sizes” (p. 4). The effect sizes in the table are all around 0.2 or lower, which implies that the relationship between personality traits with PU and PEU is small. Moreover, according to Serdar et al. (2021), “The ideal power of a study is considered to be 0.8” (p. 3). As shown in Table 4, the values for power found in this study are quite low and not close to 0.8 at all. So, the results of the post-hoc power analysis suggest that the sample size is too small to measure an effect between the relevant variables of this study (Kang, 2021). This analysis was conducted post-data-collection, to check if the acquired convenient sample was enough to find the hypothesised significance.

Table 4

Post-Hoc Power Analysis

Predictor	Cohen's *d*	Power
Predictor of PU		
Openness to Experience	-0.09	0.07
Conscientiousness	-0.27	0.28
Extraversion	0.05	0.06
Agreeableness	0.13	0.10
Neuroticism	0.21	0.19
Predictor of PEU		
Openness to Experience	-0.17	0.14
Conscientiousness	-0.05	0.06
Extraversion	0.25	0.24
Agreeableness	-0.10	0.08
Neuroticism	-0.28	0.29

Note. PU = Perceived Usefulness of technology in future careers; PEU = Perceived Ease of Use of technology in future careers. $n = 52$, $df = 50$, $\alpha = 0.05$.

Discussion

To aid Psychology students in their future careers, improve education, and contribute to academic research, this study aimed to investigate whether the Big Five personality traits of Psychology students can predict their overall acceptance of technology in their future careers. The combination of Perceived Usefulness (PU) and Perceived Ease of Use (PEU) can provide insight into general, or overall, technology acceptance (Sindermann et al., 2020). Initially, it was assumed that the traits of Openness to Experience, Conscientiousness, Extraversion, and Agreeableness have a positive relationship with PEU. Additionally, it was presumed that the trait Extraversion has a positive relationship, while Neuroticism has a negative relationship, with PU (Devaraj et al., 2008; Özbek et al., 2014; Rivers, 2021; Svendsen et al., 2013; Terzis et al., 2012). Unfortunately, none of these relationships were found to be significant in this study.

Although the relationships between the personality traits and technology acceptance in this study were not statistically significant according to the correlation and regression analyses, leading to all hypotheses being refuted, comparing this finding to previous literature on the relationships of these variables can provide valuable insights. As expected, the results of this study are not in line with previous studies, since most of them found significant relations between personality traits and technology acceptance, whether this is in the context of a specific technology or acceptance in general (Aplin-Houtz et al., 2023; Behrenbruch et al., 2013; Devaraj et al., 2008; Maican et al., 2019; Özbek et al., 2014; Sindermann et al., 2020; Svendsen et al., 2013; Weger et al., 2022). Notably, even though this study focuses on future careers and not on current technology acceptance, Weger et al. (2022) found that the chosen career field of students is “significantly related to their adoption of autonomous technology” (p. 243), which makes it difficult to argue that this can cause the lack of effect in this study.

Interestingly, within the literature, some studies reported no significance with certain traits and technology acceptance, while others did. For example, the trait Openness was found to have no significance with PU and PEU in the study of Behrenbruch et al. (2013), yet Svendsen et al. (2013) did find this significance. These two studies have in common that they were done in Northern Europe and were both about the impact of personality traits on technology acceptance in a general context. Still, the study of Behrenbruch et al. (2013) used 344 students while Svendsen et al. (2013) had 30,000 participants. Similarly, the relationship of Agreeableness on PU was not significant in the study of Özbek et al. (2014), however, it was significant in the study of Maican et al. (2019). Here, both studies were in Southeastern Europe, and about the relationship between personality traits and a certain technological application or tool. Yet, Özbek et al. (2014) comprised 401 university students, and the participants of Maican et al. (2019) were 1816 university teachers. So, the recurring theme among the studies that failed to find statistical significance seems to be a small sample size and the use of a student sample.

An additional finding that is worth mentioning, is the statistically significant negative relationship with the variable Study Year, which indicates that students who are more advanced in their academic programmes are more accepting towards technology in their future careers. The study of Nguyen et al. (2023) emphasizes this capability too, by illustrating that the students in their second and third year changed their major, as they knew more about their capabilities and what kind of career they wanted to pursue. Therefore, students in more advanced years may have a deeper understanding of technology regarding their future careers, which can result in a better conceptualisation of this variable. This can explain the statistical significance found between the variable Study Year and PU. In addition, there has already been research about the year of study acting as a moderator for attitudes about internet security, aligning broadly with this study identifying an effect of study year on technology acceptance (An et al., 2022). So, investigating the relationship with technology acceptance regarding psychology students' future careers and year of study may lead to interesting discoveries as well (An et al., 2022). All in all, the results of this study show a lack of expected relationships that may deviate from earlier findings. This can yield ground for further investigation of these variables to potentially get new insights into these relationships.

Limitations and Strengths

A possible limitation of this study is the lack of strength that was found in the reliability of the BFI-2-XS inventory. Contrary to earlier findings indicating high reliability, Cronbach's alphas for the subscales were very low (Halama et al., 2020; Rammstedt et al., 2020; Føllesdal & Soto, 2022; Attar & Ouadi, 2023). This indicates that the personality traits were not accurately represented with the 3 items that were used for each one of them. Yet, this was initially a possible strength of this inventory, since it was time-effective and efficient when being employed within a bigger questionnaire (Soto & John, 2017).

Another possible limitation is the sample size of this current study. The post-hoc power analysis already revealed that the power of both the TAM and BFI-2-XS in this study, is quite low. This indicates that an effect between the relevant variables of this study cannot be measured with a sample of 52 participants (Kang, 2021; Serdar et al., 2021). Moreover, the study of Brysbaert (2019) argues that "For many research questions, studies with less than 100 participants are underpowered" (p. 27). Not only the size, but the variety of the sample may have affected this study as well. Even though using convenience sampling may have been a simple and efficient method to gain participants, it resulted in an almost monotonous sample. Specifically, 43 (82.7%) female and 49 (94.2%) students studying at the University of Twente in the Netherlands. Furthermore, since the University of Twente is technology-oriented, and the studies that are taught there have technology integrated into them, this might affect the results by them not being representative of psychology programmes at other academic institutions. Additionally, the limited representation of male participants can affect the outcome of this study as well, since males are found to have a more positive attitude towards the use of technology (Cai et al., 2017). So, there is a limited applicability of the findings of this study, due to the low number of students from other academic institutions and students identifying with other genders.

Lastly, the concept of "technology regarding the future careers of students" may have affected the outcomes of this study. Before the whole questionnaire started, the information about the study, on the start screen asked the participants to think about the use of technology in their future jobs, all within the context of eHealth. Upon reviewing the results for the correlation analysis, it is evident that the standard deviations for PU and PEU are quite small, with averages around three, which matches the response "no comment". Even though it was utilised in another study, it lacks the same clarity as "neither agree nor disagree" and it was selected by approximately 10 (19.2%) participants for each PU and PEU question. The variation of responses and this low frequency of option three suggests that the concept of technology in future careers might have been interpreted differently by each participant. Moreover, this concept might have been too vague to imagine for the participants. According to Andrade (2021), "Variables need to be operationalized; that is, defined in a way that permits their accurate measurement" (p. 177). One final limitation of this study might be that the relationship between the variables can be partially or entirely influenced by unforeseen confounding variables (Andrade, 2021).

Recommendations for Future Research

Taking all of this together, recommendations for future research on this topic can be to include the full version of the Big Five inventory, to ascertain reliability. Additionally, a sample size with sufficient statistical power and applying random sampling instead of convenience sampling, may allow for a more diverse sample and enhance the generalisability of the results to other populations. Another suggestion for future research is to provide a more detailed description of technology regarding the future careers of psychology students, in order to give the participants a clearer understanding and visualisation of this variable. In addition, changing option three on the Likert scale of the TAM questionnaire to "neither agree nor disagree" may provide more clarity and reduce uncertainty for participants. Investigating the impact of the academic year the participants are in, and assessing the effect of any other potential confounding variables can be beneficial for future research as well. Finally, not related to personality, but it can be interesting to look at students who do not have technology in their Psychology programme since there were only three people who were not studying at the University of Twente, where it is integrated.

Conclusion

In this thesis, the research question, "Can personality traits predict the overall acceptance psychology students have for the role of technology in their future careers?" was central. The findings of this thesis indicate that the answer is no. However, this can be the case due to limitations, such as a small and monotonous sample size, an inventory with too few items assessing a construct, a vague concept of technology in future careers, ambiguous Likert scale options, or other confounding variables that are not accounted for. Overall, future research should focus on improving these limitations to find a definite answer about the prediction of personality traits on psychology student's technology acceptance regarding their future careers.

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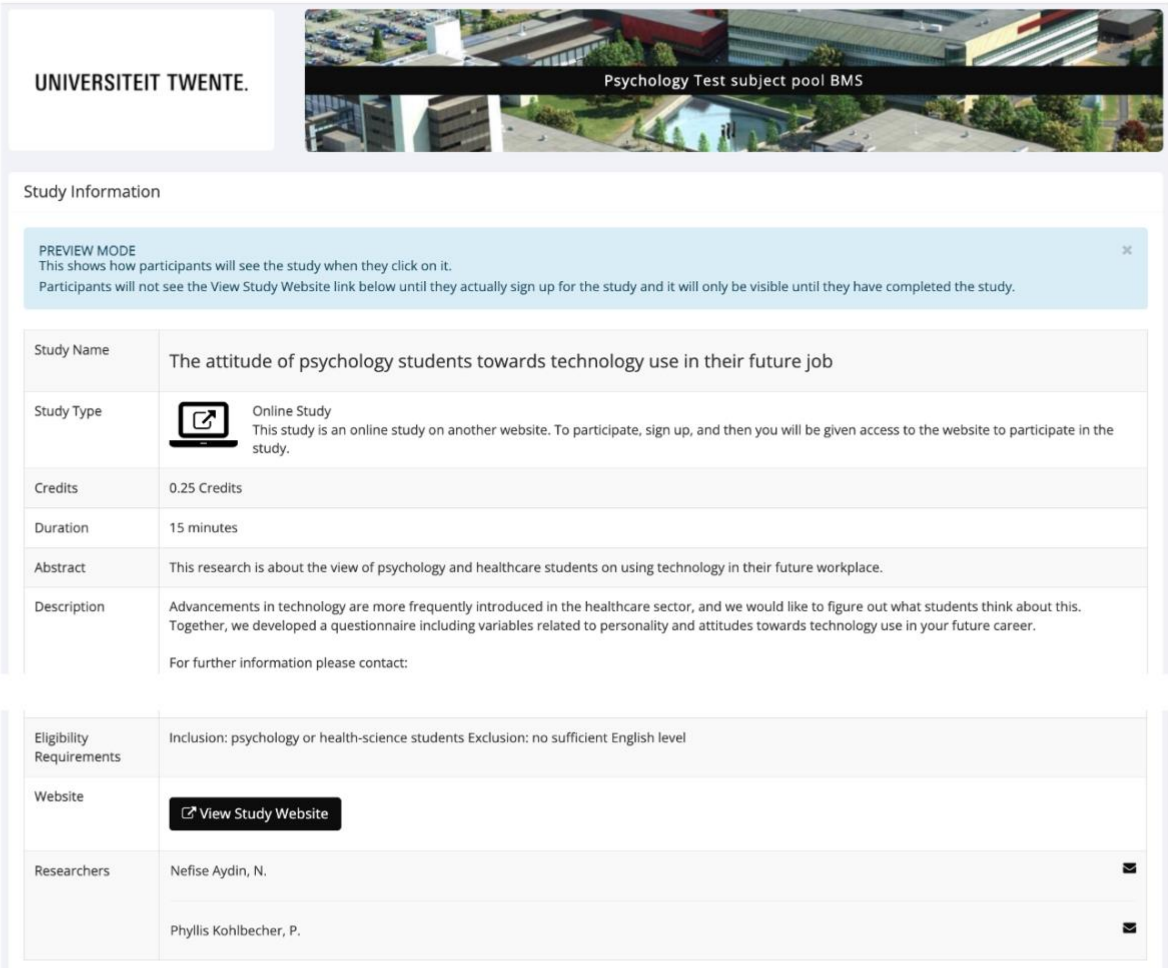
Appendix A

The Sona Page

Figure 2

Information Screen of the Study in Sona Systems



UNIVERSITEIT TWENTE.

Psychology Test subject pool BMS

Study Information

PREVIEW MODE
This shows how participants will see the study when they click on it.
Participants will not see the View Study Website link below until they actually sign up for the study and it will only be visible until they have completed the study.

Study Name	The attitude of psychology students towards technology use in their future job
Study Type	Online Study This study is an online study on another website. To participate, sign up, and then you will be given access to the website to participate in the study.
Credits	0.25 Credits
Duration	15 minutes
Abstract	This research is about the view of psychology and healthcare students on using technology in their future workplace.
Description	Advancements in technology are more frequently introduced in the healthcare sector, and we would like to figure out what students think about this. Together, we developed a questionnaire including variables related to personality and attitudes towards technology use in your future career. For further information please contact:
Eligibility Requirements	Inclusion: psychology or health-science students Exclusion: no sufficient English level
Website	View Study Website
Researchers	Nefise Aydin, N. Phyllis Kohlbecher, P.

Appendix B

The Flyer & Poster

Figure 3

Poster/Front Page of the Flyer

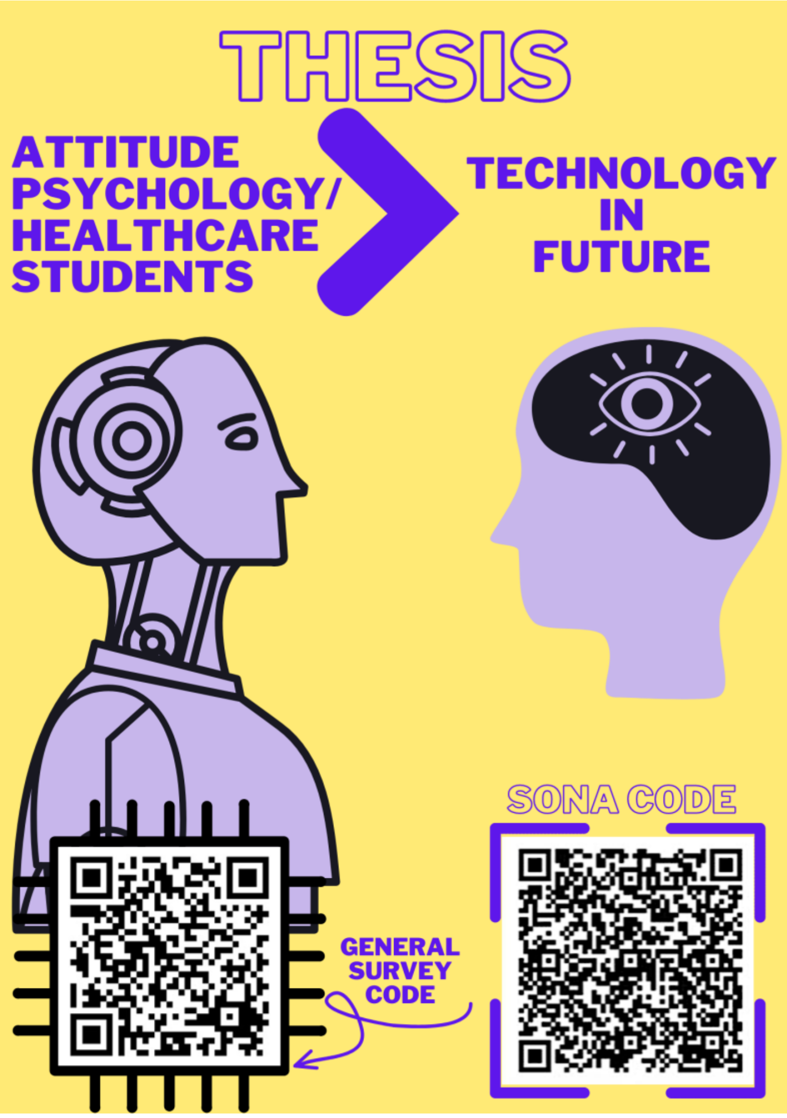


Figure 4

Back of the Flyer

Appendix C

The Entire Survey

Page 1 Information About the Study and Some Definitions

Dear Participant,

Thank you for participating in our study. Interestingly, as technology is becoming more important in the healthcare sector, we are interested in your view as a student, on the role of technology in your future job as a healthcare worker. In the survey, we include variables related to personality and attitudes towards technology use in your future career. Remember that there are no right or wrong answers, we are interested in your opinions.

There are several definitions of technology, and in connection to health, there is no consensus on which definition describes this term accordingly. Nevertheless, there is agreement that the two main components of eHealth include health and technology (Oh et al. 2005). To clarify this concept while filling in this questionnaire, please keep in mind the definition from Jiménez-Zarco et al. (2020) who define eHealth as “the use of technology to support health and well-being”.

Page 2 Informed Consent

Dear Participant,

You are being invited to participate in a research study titled “The attitude of psychology students towards technology use in their future job” This study is being done by Nefise Aydin and Phyllis Kohlbecher from the Faculty of Behavioural, Management and Social Sciences at the University of Twente.

The purpose of this research study is to look into to what extent psychology students embrace technology in their future careers, and will take you approximately 10-15 minutes to complete. The data will be used for the bachelor theses of the researchers.

Your participation in this study is entirely voluntary and you can withdraw at any time. You are free to omit any question. We believe there are no known risks associated with this research study. To the best of our ability, your answers in this study will remain confidential. We will minimize any risks by not collecting any personally identifiable information to ensure anonymity and confidentiality. (carefully storing and handling the data)

Study contact details for further information:

Phyllis Kohlbecher,

Nefise Aydin,

I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and that I can withdraw from the study at any time, without having to give a reason.

○ Yes

○ No

Page 3 Demographic Questions

What is your age?

○ (select from 16-100)

What is your gender?

○ Male

○ Female

○ Non-binary / third gender

○ Prefer not to say

What is your nationality?

○ Dutch

○ German

○ Other

If selected other, where are you from?

○ (text option)

What do you study?

○ Psychology

○ Health-related study

○ Non health-related study

Do you study at the University of Twente?

○ Yes

○ No

Do you have technology included in your studies?

○ Yes

○ No

If you study psychology, what specific type of psychologist do you aspire to become in the future (e.g. clinical psychologist, researcher, etc.)

○ (text option)

What year of your academic programme are you currently in? (If you repeated a year, choose the year of your program that you are primarily enrolled in)

○ (select from 1st-year bachelor, 2nd-year bachelor, 3rd-year bachelor, 4th-year bachelor, 1st-year masters & 2nd-year masters)

Page 4 Part of Another Study

In the following, you are asked to answer a few questions. Please select the answer that first comes to mind, there are no right or wrong answers. (Answer options: Does not apply at all, Rather does not apply, Rather applies & Applies exactly)

I always want to try new things.

I am a curious person.

I travel a lot to get to know new cultures.

I would prefer everything to stay as it is.

I like to discuss things.

I always enjoy learning new things.

In my free time, I love to spend time with art, music, and literature.

I am very interested in philosophical questions.

I read a lot about scientific topics, new discoveries, or historical events.

I have many ideas and a vast imagination

Page 5 BFI-2-XS

Please take a moment to choose the answer that first comes to mind when considering the following prompt: I am someone who…

(Answer options: Disagree strongly, Disagree a little, Neutral; no opinion, Agree a little & Agree strongly)

1. __ Tends to be quiet.
2. __ Is compassionate, has a soft heart.
3. __ Tends to be disorganized.
4. __ Worries a lot.
5. __ Is fascinated by art, music, or literature.
6. __ Is dominant, acts as a leader.
7. __ Is sometimes rude to others.
8. __ Has difficulty getting started on tasks.
9. __ Tends to feel depressed, blue.
10. __ Has little interest in abstract ideas.
11. __ Is full of energy.
12. __ Assumes the best about people.
13. __ Is reliable, can always be counted on.
14. __ Is emotionally stable, not easily upset.
15. __ Is original, comes up with new ideas.

Page 6 Part of Another Study

(Answer options: Strongly Disagree, Disagree, Neither Agree nor Disagree, Agree & Strongly Agree)

Technology is my friend ...

I enjoy learning new computer programs and hearing about new technologies.

People expect me to know about technology and I don’t want to let them down.

If I am given an assignment that requires that I learn to use a new program or how to use a machine, I usually succeed.

I relate well to technology and machines.

I am comfortable learning new technology.

I know how to deal with technological malfunctions or problems.

Solving a technological problem seems like a fun challenge.

I find most technology easy to learn.

I feel as up-to-date on technology as my peers.

Page 7 Technology Acceptance Model (TAM) Model

Please answer the last few questions of this survey.

(Answer options: strongly agree, agree, no comment, disagree & strongly disagree)

1. Using technology in my future job will enable me to accomplish tasks more quickly.
2. Using technology will improve my job performance in the future.
3. Using technology in my future job will increase my productivity.
4. Using technology will enhance my effectiveness on the future job.
5. Using technology will make it easier to do my future job.
6. I find technology useful in my future job.
7. Learning to use technology in my future job will be easy for me.
8. I will find it easy to get technology to do what I want it to do in my future job.

9. My interaction with technology in my future job will be clear and understandable.
10. I will find technology in my future job to be flexible to interact with.
11. It will be easy for me to become skillful in using technology at my future job.
12. I will find technology in my future job to be easy to use.

Page 8 Final page after completing the survey

We thank you for your time spent taking this survey.

Your response has been recorded.

Appendix D

Assumptions

Figure 5

Normality Histogram PU

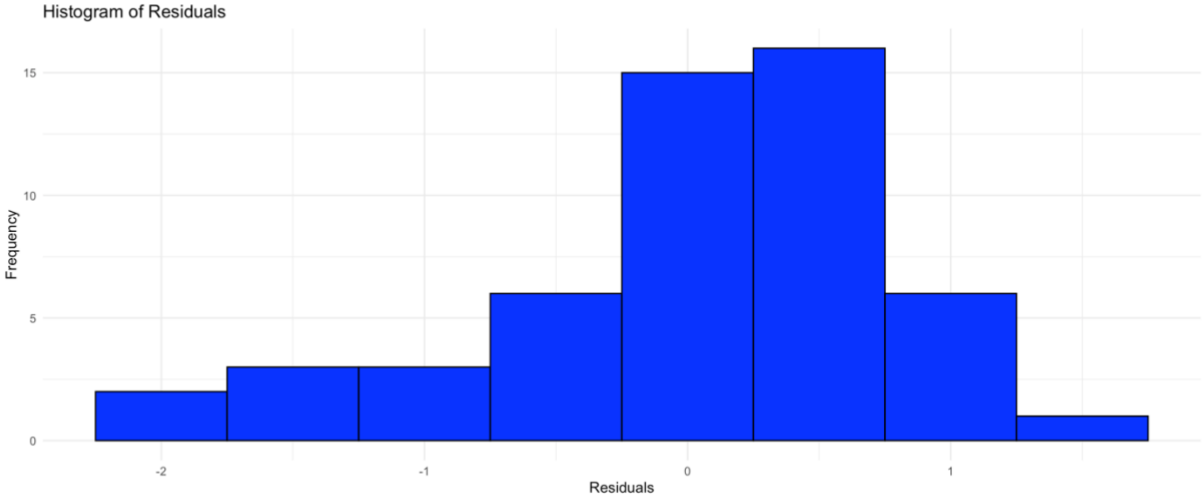


Figure 6

Scatterplot for Homoscedasticity and Linearity PU

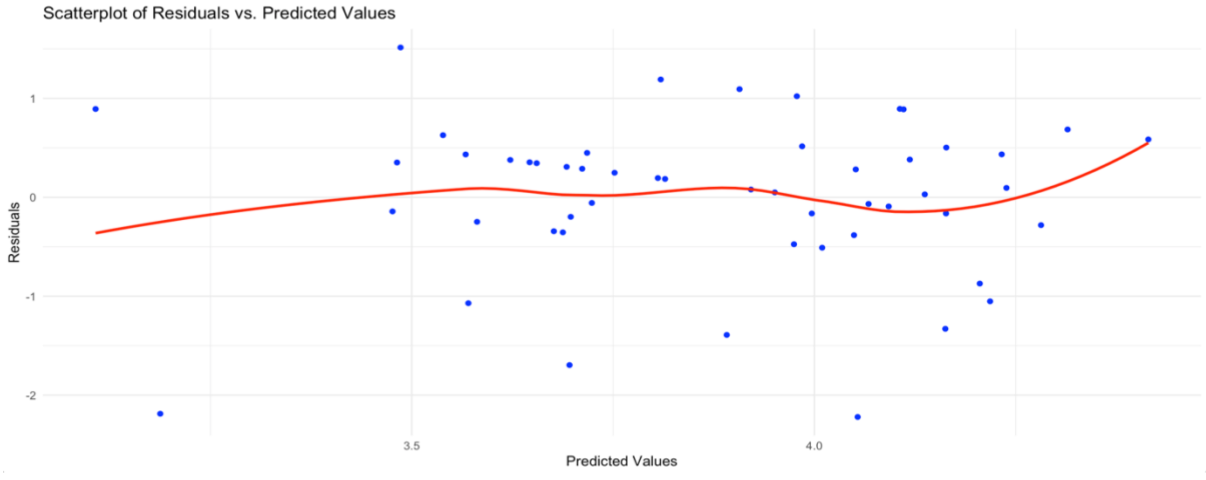


Figure 7

Normality Histogram PEU

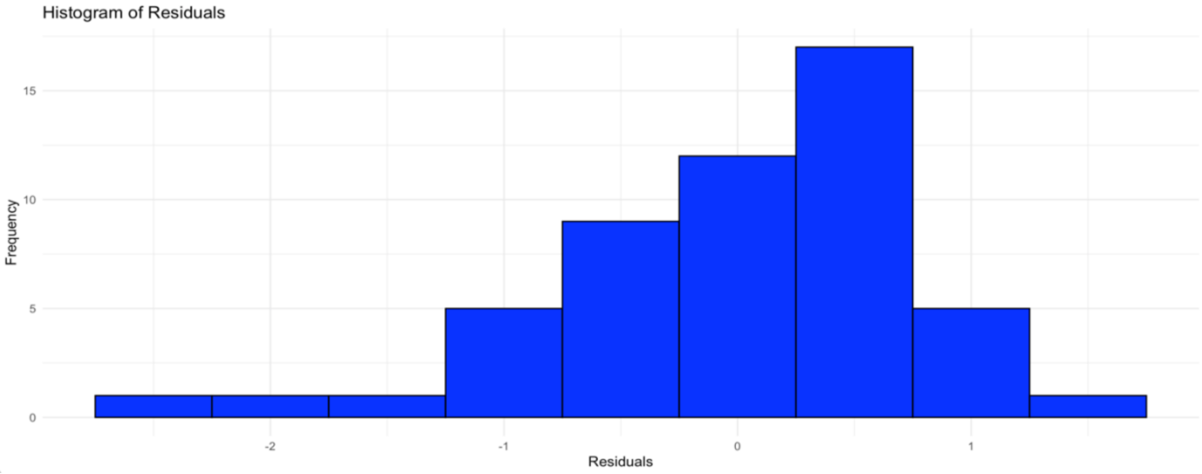
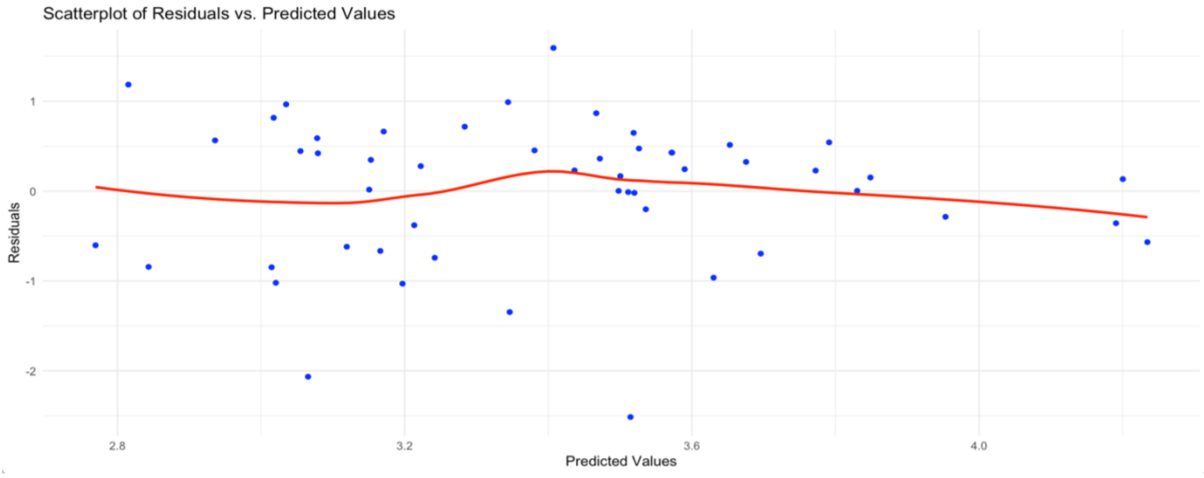


Figure 8

Scatterplot for Homoscedasticity and Linearity PEU



Appendix E

The R Script

```
#Bachelor thesis results
#Nefise Aydin
#11/06/2024

install.packages("psych")
install.packages("tidyverse")
install.packages("foreign")
install.packages("lme4")
install.packages("lmerTest")
install.packages("modelr")
install.packages("broom")
install.packages("Hmisc")
install.packages("Kendall")
install.packages("janitor")
install.packages("dplyr")
install.packages("ggplot2")
install.packages("pwr")

library(pwr)
library(dplyr)
library(janitor)
library(Kendall)
```

```
library(Hmisc)
library(tidyverse)
library(foreign)
library(lme4)
library(lmerTest)
library(modelr)
library(broom)
library(ggplot2)
library(psych)

#Setting working directory
setwd("/Users/na/Downloads")

#Importing data
data <- read.csv("Data_Bachelor Thesis_Nefise Aydin.csv")

#Remove responses to other questionnaires
data1 <- data %>%
  select(-X1.Opennes, -X2.Opennes, -X3.Opennes, -X4.Opennes, -X5.Opennes,
         -X6.Opennes, -X7.Opennes, -X8.Opennes, -X9.Opennes, -X10.Opennes,
         -X1.Affinity, -X2.Affinity, -X3.Affinity, -X4.Affinity, -X5.Affinity,
         -X6.Affinity, -X7.Affinity, -X8.Affinity, -X9.Affinity, -X10.Affinity)

#Remove first 2 columns with repetition of the titles & get the order to start from 1
data1 <- data1[-c(1:2),]
```

```
row.names(data1) <- NULL

#Remove redundant information
data1 <- data1 %>%
  select(-StartDate, -EndDate, -Status, -IPAddress, -RecordedDate, -ResponseId,
         -RecipientLastName, -RecipientFirstName, -RecipientEmail, -ExternalReference,
         -LocationLatitude, -LocationLongitude, -DistributionChannel, -UserLanguage)

#Filter for psychology students only
data1 <- data1 %>% filter(Study == "Psychology")

#Keep everyone who gave consent and answered both questionnaires entirely
data1 <- data1 %>% filter(giving.consent == "Yes")

data1 <- data1[complete.cases(data1[, c("Personality.1", "Personality.2", "Personality.3",
                                        "Personality.4", "Personality.5", "Personality.6",
                                        "Personality.7", "Personality.8", "Personality.9",
                                        "Personality.10", "Personality.11", "Personality.12",
                                        "Personality.13", "Personality.14", "Personality.15",
                                        "PU1", "PU2", "PU3", "PU4", "PU5", "PU6", "PEU1",
                                        "PEU2", "PEU3", "PEU4", "PEU5", "PEU6")]), ]

#Mean + SD + minimum + maximum of age (by 1st making no response into NA) & Mean
duration of the survey (in seconds)
```

```
data1$age[data1$age == ""] <- NA
data_without_missing_age <- na.omit(data1$age)
data_without_missing_age <- as.numeric(data_without_missing_age)
mean(data_without_missing_age, na.rm = TRUE)
view(data_without_missing_age)

sd(data_without_missing_age, na.rm = TRUE)

min(data_without_missing_age, na.rm = TRUE)

max(data_without_missing_age, na.rm = TRUE)

data_duration <- na.omit(data1$Duration..in.seconds.)
data_duration <- as.numeric(data_duration)
mean(data_duration, na.rm = TRUE)
view(data_duration)

#Gender data
gender_summary <- table(data1$gender)
view(gender_summary)

#Nationality data
nationality_summary <- table(data1$nationality)
view(nationality_summary)
```

```
#Future job interest
futurejob_summary <- table(data1$Job.choice)
view(futurejob_summary)

#Study year
Study_year_summary <- table(data1$X.Year.of.Study)
view(Study_year_summary)

#Utwente
Student_UT_summary <- table(data1$Uni)
view(Student_UT_summary)

#Putting the answers to the items into a Likert scale with numbers
response_mapping <- c("Disagree strongly" = 1, "Disagree a little" = 2,
                      "Neutral; no opinion" = 3, "Agree a little" = 4,
                      "Agree strongly" = 5)

items_BFI_2_XS <- c("Personality.1", "Personality.2", "Personality.3",
                    "Personality.4", "Personality.5", "Personality.6",
                    "Personality.7", "Personality.8", "Personality.9",
                    "Personality.10", "Personality.11", "Personality.12",
                    "Personality.13", "Personality.14", "Personality.15")

data1 <- data1 %>%
  mutate(across(all_of(items_BFI_2_XS), ~as.numeric(recode(., !!!response_mapping))))
```

```
response_mapping2 <- c("strongly agree" = 5, "agree" = 4,
                       "no comment" = 3, "disagree" = 2,
                       "strongly disagree" = 1)

items_TAM <- c("PU1", "PU2", "PU3", "PU4", "PU5", "PU6",
               "PEU1", "PEU2", "PEU3", "PEU4", "PEU5", "PEU6")

data1 <- data1 %>%
  mutate(across(all_of(items_TAM), ~as.numeric(recode(., !!!response_mapping2))))

#Reverse coding items 1, 3, 7, 8, 10 & 14 from the BFI-2-XS

reverse_items <- c("Personality.1", "Personality.3", "Personality.7",
                   "Personality.8", "Personality.10", "Personality.14")

data1 <- data1 %>%
  mutate(across(all_of(reverse_items), ~6 - .))

#Check if there are missing values, here 8 people didn't state their age

missing_values <- colSums(is.na(data1))
view(missing_values)

#Results: Cronbach's alpha questionnaire TAM = 0.94
```

```
data1 %>%
  select("PU1", "PU2", "PU3", "PU4", "PU5", "PU6", "PEU1",
         "PEU2", "PEU3", "PEU4", "PEU5", "PEU6") %>%
  alpha()

#Results: PU Cronbach's alpha questionnaire = 0.94 & correlation

data1 %>%
  select("PU1", "PU2", "PU3", "PU4", "PU5", "PU6") %>%
  alpha()

data1 %>%
  select("PU1", "PU2", "PU3", "PU4", "PU5", "PU6") %>%
  cor()

#Results: PEU Cronbach's alpha questionnaire = 0.94 & correlation

data1 %>%
  select("PEU1", "PEU2", "PEU3", "PEU4", "PEU5", "PEU6") %>%
  alpha()

data1 %>%
  select("PEU1", "PEU2", "PEU3", "PEU4", "PEU5", "PEU6") %>%
  cor()
```

```
#Results: Cronbach's alpha questionnaire BFI-2-XS = 0.48

data1 %>%
  select("Personality.1", "Personality.2", "Personality.3",
         "Personality.4", "Personality.5", "Personality.6",
         "Personality.7", "Personality.8", "Personality.9",
         "Personality.10", "Personality.11", "Personality.12",
         "Personality.13", "Personality.14", "Personality.15") %>%
  alpha()

#Results: Cronbach's alpha questionnaire BFI-2-XS if you drop item 4, 9 & 14 (neuroticism)
= 0.58

data1 %>%
  select("Personality.1", "Personality.2", "Personality.3",
         "Personality.5", "Personality.6",
         "Personality.7", "Personality.8",
         "Personality.10", "Personality.11", "Personality.12",
         "Personality.13", "Personality.15") %>%
  alpha()

#Results: Openness Cronbach's alpha = 0.49 & correlation

data1 %>%
```

```
  select("Personality.5", "Personality.10", "Personality.15") %>%
  alpha()

data1 %>%
  select("Personality.5", "Personality.10", "Personality.15") %>%
  cor()

#Results: Conscientiousness Cronbach's alpha = 0.62 & correlation

data1 %>%
  select("Personality.3", "Personality.8", "Personality.13") %>%
  alpha()

data1 %>%
  select("Personality.3", "Personality.8", "Personality.13") %>%
  cor()

#Results: Extraversion Cronbach's alpha = 0.55 & correlation

data1 %>%
  select("Personality.1", "Personality.6", "Personality.11") %>%
  alpha()

data1 %>%
  select("Personality.1", "Personality.6", "Personality.11") %>%
```

```
  cor()

data1 %>%
  select("Personality.1", "Personality.11") %>%
  cor()

data1 %>%
  select("Personality.1", "Personality.6") %>%
  cor()

#Results: Agreeableness Cronbach's alpha = 0.53 & correlation

data1 %>%
  select("Personality.2", "Personality.7", "Personality.12") %>%
  alpha()

data1 %>%
  select("Personality.2", "Personality.7", "Personality.12") %>%
  cor()

#Results: Neuroticism Cronbach's alpha = 0.66 & correlation

data1 %>%
  select("Personality.4", "Personality.9", "Personality.14") %>%
  alpha()
```

```
data1 %>%
  select("Personality.4", "Personality.9", "Personality.14") %>%
  cor()

# Results: correlation questionnaire BFI-2-XS
data1 %>%
  select("Personality.1", "Personality.2", "Personality.3",
         "Personality.4", "Personality.5", "Personality.6",
         "Personality.7", "Personality.8", "Personality.9",
         "Personality.10", "Personality.11", "Personality.12",
         "Personality.13", "Personality.14", "Personality.15") %>%
  cor()

#Results: correlation questionnaire TAM
#(PU items have high correlations with each other and the other items associated to PEU too)

data1 %>%
  select("PU1", "PU2", "PU3", "PU4", "PU5", "PU6", "PEU1",
         "PEU2", "PEU3", "PEU4", "PEU5", "PEU6") %>%
  cor()

data1 %>%
  select("PU1", "PU2", "PU3", "PU4", "PU5", "PU6", "PEU1",
         "PEU2", "PEU3", "PEU4", "PEU5", "PEU6") %>%
```

```
  cor()

#correlation table all items (personality & technology acceptance)
cor(data1[, c("Personality.1", "Personality.2", "Personality.3",
          "Personality.4", "Personality.5", "Personality.6",
          "Personality.7", "Personality.8", "Personality.9",
          "Personality.10", "Personality.11", "Personality.12",
          "Personality.13", "Personality.14", "Personality.15",
          "PU1", "PU2", "PU3", "PU4", "PU5", "PU6",
          "PEU1", "PEU2", "PEU3", "PEU4", "PEU5", "PEU6")])

#Results: mean for each item questionnaire BFI-2-XS

data1 %>%
  select("Personality.1", "Personality.2", "Personality.3",
       "Personality.4", "Personality.5", "Personality.6",
       "Personality.7", "Personality.8", "Personality.9",
       "Personality.10", "Personality.11", "Personality.12",
       "Personality.13", "Personality.14", "Personality.15") %>%
  colMeans()

#Results: mean & other stats for each trait of questionnaire BFI-2-XS

Openness <- colMeans(data1[, c("Personality.5", "Personality.10", "Personality.15")], na.rm
= TRUE)
```

```
Conscientiousness <- colMeans(data1[, c("Personality.3", "Personality.8", "Personality.13")],
na.rm = TRUE)
Extraversion <- colMeans(data1[, c("Personality.1", "Personality.6", "Personality.11")],
na.rm = TRUE)
Agreeableness <- colMeans(data1[, c("Personality.2", "Personality.7", "Personality.12")],
na.rm = TRUE)
Neuroticism <- colMeans(data1[, c("Personality.4", "Personality.9", "Personality.14")], na.rm
= TRUE)

mean(Openness)
sd(Openness)
min(Openness)
max(Openness)
median(Openness)
mean(Conscientiousness)
sd(Conscientiousness)
min(Conscientiousness)
max(Conscientiousness)
median(Conscientiousness)
mean(Extraversion)
sd(Extraversion)
min(Extraversion)
max(Extraversion)
median(Extraversion)
mean(Agreeableness)
```

```
sd(Agreeableness)

min(Agreeableness)

max(Agreeableness)

median(Agreeableness)

mean(Neuroticism)

sd(Neuroticism)

min(Neuroticism)

max(Neuroticism)

median(Neuroticism)


#Results: mean for entire questionnaire BFI-2-XS

mean_entire_BFI_2_XS <- colMeans(data1[, c("Personality.1", "Personality.2",
"Personality.3",
                              "Personality.4", "Personality.5", "Personality.6",
                              "Personality.7", "Personality.8", "Personality.9",
                              "Personality.10", "Personality.11", "Personality.12",
                              "Personality.13", "Personality.14", "Personality.15")], na.rm =
TRUE)

mean(mean_entire_BFI_2_XS)


#Results: mean for each item questionnaire TAM


data1 %>%
  select("PU1", "PU2", "PU3", "PU4", "PU5", "PU6", "PEU1",
       "PEU2", "PEU3", "PEU4", "PEU5", "PEU6") %>%
```

```
  colMeans()

#Results: mean & stats for each subscale (PU & PEU) questionnaire TAM

PU <- colMeans(data1[, c("PU1", "PU2", "PU3", "PU4", "PU5", "PU6")], na.rm = TRUE)
PEU <- colMeans(data1[, c("PEU1", "PEU2", "PEU3", "PEU4", "PEU5", "PEU6")], na.rm =
TRUE)

mean(PU)
sd(PU)
min(PU)
max(PU)
median(PU)
mean(PEU)
sd(PEU)
min(PEU)
max(PEU)
median(PEU)

#Results: mean for entire questionnaire TAM

mean_entire_TAM <- colMeans(data1[, c("PU1", "PU2", "PU3", "PU4", "PU5", "PU6",
"PEU1",
                                     "PEU2", "PEU3", "PEU4", "PEU5", "PEU6")], na.rm = TRUE)
mean(mean_entire_TAM)
```

```
#Results:scale analyses; SD Items BFI-2-XS
sapply(data1[, c("Personality.1", "Personality.2", "Personality.3",
        "Personality.4", "Personality.5", "Personality.6",
        "Personality.7", "Personality.8", "Personality.9",
        "Personality.10", "Personality.11", "Personality.12",
        "Personality.13", "Personality.14", "Personality.15")], sd, na.rm = TRUE)

#SD for whole BFI-2-XS
sqrt(mean(sapply(data1[, paste0("Personality.", 1:15)], sd, na.rm = TRUE)^2))

#Results:scale analyses; SD Items TAM
sapply(data1[, c("PU1", "PU2", "PU3", "PU4", "PU5", "PU6", "PEU1",
        "PEU2", "PEU3", "PEU4", "PEU5", "PEU6")], sd, na.rm = TRUE)


#SD for whole TAM
sqrt(mean(sapply(data1[, c("PU1", "PU2", "PU3", "PU4", "PU5", "PU6", "PEU1",
             "PEU2", "PEU3", "PEU4", "PEU5", "PEU6")], sd, na.rm = TRUE)^2))

#Results: min. and max. scores of each item (BFI-2-XS & TAM)

data1 %>%
  select("Personality.1", "Personality.2", "Personality.3",
     "Personality.4", "Personality.5", "Personality.6",
```

```
        "Personality.7", "Personality.8", "Personality.9",
        "Personality.10", "Personality.11", "Personality.12",
        "Personality.13", "Personality.14", "Personality.15",
        "PU1", "PU2", "PU3", "PU4", "PU5", "PU6", "PEU1",
        "PEU2", "PEU3", "PEU4", "PEU5", "PEU6") %>%
  summarise_all(min, na.rm = TRUE)

data1 %>%
  select("Personality.1", "Personality.2", "Personality.3",
        "Personality.4", "Personality.5", "Personality.6",
        "Personality.7", "Personality.8", "Personality.9",
        "Personality.10", "Personality.11", "Personality.12",
        "Personality.13", "Personality.14", "Personality.15",
        "PU1", "PU2", "PU3", "PU4", "PU5", "PU6", "PEU1",
        "PEU2", "PEU3", "PEU4", "PEU5", "PEU6") %>%
  summarise_all(max, na.rm = TRUE)

#Results: correlation table all traits, PU & PEU (personality & technology acceptance)

data1$model_Openness <- rowMeans(data1[, c("Personality.5", "Personality.10",
"Personality.15")])
data1$model_Conscientiousness <- rowMeans(data1[, c("Personality.3", "Personality.8",
"Personality.13")])
data1$model_Extraversion <- rowMeans(data1[, c("Personality.1", "Personality.6",
"Personality.11")])
```

```
data1$model_Agreeableness <- rowMeans(data1[, c("Personality.2", "Personality.7",
"Personality.12")])
data1$model_Neuroticism <- rowMeans(data1[, c("Personality.4", "Personality.9",
"Personality.14")])
data1$mean_model_PU <- rowMeans(data1[, c("PU1", "PU2", "PU3",
                                  "PU4", "PU5", "PU6")])
data1$mean_model_PEU <- rowMeans(data1[, c("PEU1", "PEU2", "PEU3",
                                   "PEU4", "PEU5", "PEU6")])

cor(data1[, c("model_Openness", "model_Conscientiousness", "model_Extraversion",
"model_Agreeableness",
          "model_Neuroticism", "mean_model_PU", "mean_model_PEU")])

#Results: correlation table all traits, PU, PEU, gender, nationality, etc. + p-values

data1$male <- ifelse(data1$gender == "Male", 1, 0)
data1$female <- ifelse(data1$gender == "Female", 1, 0)
data1$Dutch <- ifelse(data1$nationality == "Dutch", 1, 0)
data1$German <- ifelse(data1$nationality == "German", 1, 0)
data1$firstandsecondYears <- ifelse(data1$X.Year.of.Study %in% c("1st-year bachelor",
"2nd-year bachelor"), 1, 0)
data1$higherYears <- ifelse(data1$X.Year.of.Study %in% c("3rd-year bachelor", "4th-year
bachelor", "1st-year masters"), 1, 0)
data1$clinical_dummy <- ifelse(grepl("clinical", tolower(data1$Job.choice)), 1, 0)
data1$non_clinical_dummy <- ifelse(!grepl("clinical", tolower(data1$Job.choice)), 1, 0)
```

```
data1$Dummy_StudyYears <- ifelse(data1$X.Year.of.Study %in% c("1st-year bachelor",
"2nd-year bachelor"), 1, 0)
data1$Dummy_ClinicalCareerAspiration <- ifelse(grepl("clinical",
tolower(data1$Job.choice)), 1, 0)

mean(data1$male)
sd(data1$male)
min(data1$male)
max(data1$male)
median(data1$male)

mean(data1$female)
sd(data1$female)
min(data1$female)
max(data1$female)
median(data1$female)

mean(data1$Dutch)
sd(data1$Dutch)
min(data1$Dutch)
max(data1$Dutch)
median(data1$Dutch)

mean(data1$German)
sd(data1$German)
```

```
min(data1$German)
max(data1$German)
median(data1$German)

mean(data1$Dummy_StudyYears)
sd(data1$Dummy_StudyYears)
min(data1$Dummy_StudyYears)
max(data1$Dummy_StudyYears)
median(data1$Dummy_StudyYears)

mean(data1$Dummy_ClinicalCareerAspiration)
sd(data1$Dummy_ClinicalCareerAspiration)
min(data1$Dummy_ClinicalCareerAspiration)
max(data1$Dummy_ClinicalCareerAspiration)
median(data1$Dummy_ClinicalCareerAspiration)

cor(data1[, c("model_Openness", "model_Conscientiousness", "model_Extraversion",
"model_Agreeableness",
        "model_Neuroticism", "mean_model_PU", "mean_model_PEU", "female", "male",
"Dutch",
        "German", "Dummy_StudyYears", "Dummy_ClinicalCareerAspiration")])

variables <- c("model_Openness", "model_Conscientiousness", "model_Extraversion",
"model_Agreeableness",
```

```
        "model_Neuroticism", "mean_model_PU", "mean_model_PEU", "female", "male",
"Dutch",
        "German", "Dummy_StudyYears", "Dummy_ClinicalCareerAspiration")

correlation_matrix <- matrix(NA, ncol = length(variables), nrow = length(variables))
p_value_matrix <- matrix(NA, ncol = length(variables), nrow = length(variables))
rownames(correlation_matrix) <- colnames(p_value_matrix) <- variables
colnames(correlation_matrix) <- colnames(p_value_matrix) <- variables

for (i in 1:(length(variables) - 1)) {
  for (j in (i+1):length(variables)) {

    var1 <- data1[[variables[i]]]
    var2 <- data1[[variables[j]]]

    complete_cases <- complete.cases(var1, var2)
    var1 <- var1[complete_cases]
    var2 <- var2[complete_cases]

    correlation_result <- cor.test(var1, var2, method = "pearson")

    correlation_matrix[i, j] <- correlation_matrix[j, i] <- correlation_result$estimate
    p_value_matrix[i, j] <- p_value_matrix[j, i] <- correlation_result$p.value
  }
}
```

```
View(correlation_matrix)
View(p_value_matrix)

#Assumptions PU; Fit your regression model (example: lm(y ~ x1 + x2, data = data1))
model_assumptions_PU <- lm(mean_model_PU ~ model_Openness +
model_Conscientiousness
                        + model_Extraversion + model_Agreeableness + model_Neuroticism
                        , data = data1)

#Assumptions PU;  Calculate residuals and predicted values
residuals1 <- resid(model_assumptions_PU)
predicted1 <- predict(model_assumptions_PU)

#Assumptions PU; Create a data frame with residuals and predicted values
data2 <- data.frame(residuals1, predicted1)

#Assumptions PU: Plot 1: Histogram for normality of residuals
ggplot(data2, aes(x = residuals1)) +
  geom_histogram(binwidth = 0.5, color = "black", fill = "blue") +
  labs(title = "Histogram of Residuals", x = "Residuals", y = "Frequency") +
  theme_minimal()

#Assumptions PU: Plot 2: Scatterplot for homoscedasticity and linearity
ggplot(data2, aes(x = predicted1, y = residuals1)) +
```

```
  geom_point(color = "blue") +
  geom_smooth(method = "loess", color = "red", se = FALSE) +
  labs(title = "Scatterplot of Residuals vs. Predicted Values",
       x = "Predicted Values",
       y = "Residuals") +
  theme_minimal()

#Assumptions PEU; Fit your regression model (example: lm(y ~ x1 + x2, data = data1))
model_assumptions_PEU <- lm(mean_model_PEU ~ model_Openness +
model_Conscientiousness
                        + model_Extraversion + model_Agreeableness + model_Neuroticism,
                        data = data1)

#Assumptions PEU;  Calculate residuals and predicted values
residuals2 <- resid(model_assumptions_PEU)
predicted2 <- predict(model_assumptions_PEU)

#Assumptions PEU; Create a data frame with residuals and predicted values
data3 <- data.frame(residuals2, predicted2)

#Assumptions PEU: Plot 1: Histogram for normality of residuals
ggplot(data3, aes(x = residuals2)) +
  geom_histogram(binwidth = 0.5, color = "black", fill = "blue") +
  labs(title = "Histogram of Residuals", x = "Residuals", y = "Frequency") +
  theme_minimal()
```

```
#Assumptions PEU: Plot 2: Scatterplot for homoscedasticity and linearity
ggplot(data3, aes(x = predicted2, y = residuals2)) +
  geom_point(color = "blue") +
  geom_smooth(method = "loess", color = "red", se = FALSE) +
  labs(title = "Scatterplot of Residuals vs. Predicted Values",
       x = "Predicted Values",
       y = "Residuals") +
  theme_minimal()

#Results: regression analysis BFI-2-XS effects on TAM (= PU & PEU)

data1$mean_model_PU_PEU <- rowMeans(data1[, c("PU1", "PU2", "PU3",
                                    "PU4", "PU5", "PU6",
                                    "PEU1", "PEU2", "PEU3",
                                    "PEU4", "PEU5", "PEU6")])

data1$mean_model_BFI2XS <- rowMeans(data1[, c("Personality.1", "Personality.2",
"Personality.3",
                                    "Personality.4", "Personality.5", "Personality.6",
                                    "Personality.7", "Personality.8", "Personality.9",
                                    "Personality.10", "Personality.11", "Personality.12",
                                    "Personality.13", "Personality.14", "Personality.15")])
```

```
model1 <- lm(mean_model_PU_PEU ~ mean_model_BFI2XS,
        data = data1)
summary(model1)



#Results: regression analysis BFI-2-XS effects on PU
model2 <- lm(mean_model_PU ~ mean_model_BFI2XS,
        data = data1)
summary(model2)

#Results: regression analysis BFI-2-XS effects on PEU
model3 <- lm(mean_model_PEU ~ mean_model_BFI2XS,
        data = data1)
summary(model3)



#Results: regression analysis Openness on whole TAM (= PU & PEU) & PU & PEU)
model4 <- lm(mean_model_PU_PEU ~ model_Openness, data = data1)
summary(model4)

model5 <- lm(mean_model_PU ~ model_Openness, data = data1)
summary(model5)
confint(model5)

model6 <- lm(mean_model_PEU ~ model_Openness, data = data1)
```

```
summary(model6)
confint(model6)

#Results: regression analysis whole trait Conscientiousness on whole TAM (= PU & PEU) & PU & PEU)
model7 <- lm(mean_model_PU_PEU ~ model_Conscientiousness, data = data1)
summary(model7)

model8 <- lm(mean_model_PU ~ model_Conscientiousness, data = data1)
summary(model8)
confint(model8)

model9 <- lm(mean_model_PEU ~ model_Conscientiousness, data = data1)
summary(model9)
confint(model9)

#Results: regression analysis whole trait Extraversion on whole TAM (= PU & PEU) & PU & PEU)
model10 <- lm(mean_model_PU_PEU ~ model_Extraversion, data = data1)
summary(model10)

model11 <- lm(mean_model_PU ~ model_Extraversion, data = data1)
summary(model11)
confint(model11)
```

```
model12 <- lm(mean_model_PEU ~ model_Extraversion, data = data1)
summary(model12)
confint(model12)

#Results: regression analysis whole trait Agreeableness on whole TAM (= PU & PEU) & PU & PEU)
model13 <- lm(mean_model_PU_PEU ~ model_Agreeableness, data = data1)
summary(model13)

model14 <- lm(mean_model_PU ~ model_Agreeableness, data = data1)
summary(model14)
confint(model14)

model15 <- lm(mean_model_PEU ~ model_Agreeableness, data = data1)
summary(model15)
confint(model15)

#Results: regression analysis whole trait Neuroticism on whole TAM (= PU & PEU) & PU & PEU)
model16 <- lm(mean_model_PU_PEU ~ model_Neuroticism, data = data1)
summary(model16)

model17 <- lm(mean_model_PU ~ model_Neuroticism, data = data1)
summary(model17)
confint(model17)
```

```
model18 <- lm(mean_model_PEU ~ model_Neuroticism, data = data1)

summary(model18)

confint(model18)


#Post-Hoc Power Analysis Openness on PU

pwr.t.test(n = 52, d = -0.09, sig.level = 0.05, alternative = "two.sided")


#Post-Hoc Power Analysis Openness on PEU

pwr.t.test(n = 52, d = -0.17, sig.level = 0.05, alternative = "two.sided")


#Post-Hoc Power Analysis Conscientiousness on PU

pwr.t.test(n = 52, d = -0.27, sig.level = 0.05, alternative = "two.sided")


#Post-Hoc Power Analysis Conscientiousness on PEU

pwr.t.test(n = 52, d = -0.05, sig.level = 0.05, alternative = "two.sided")


#Post-Hoc Power Analysis Extraversion on PU

pwr.t.test(n = 52, d = 0.05, sig.level = 0.05, alternative = "two.sided")


#Post-Hoc Power Analysis Extraversion on PEU

pwr.t.test(n = 52, d = 0.25, sig.level = 0.05, alternative = "two.sided")


#Post-Hoc Power Analysis Agreeableness on PU

pwr.t.test(n = 52, d = 0.13, sig.level = 0.05, alternative = "two.sided")
```

```
#Post-Hoc Power Analysis Agreeableness on PEU

pwr.t.test(n = 52, d = -0.10, sig.level = 0.05, alternative = "two.sided")


#Post-Hoc Power Analysis Neuroticism on PU

pwr.t.test(n = 52, d = 0.21, sig.level = 0.05, alternative = "two.sided")


#Post-Hoc Power Analysis Neuroticism on PEU

pwr.t.test(n = 52, d = -0.28, sig.level = 0.05, alternative = "two.sided")
```