Does workplace autonomy, workplace relatedness, and general competence, as conceptualized in Self-Determination Theory, influence employees' positive affect?

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Executive Summary

Evidence shows that Self-Determination Theory (SDT) is a robust and effective framework for understanding human motivation and well-being, particularly in workplace settings (Deci, 2000). This study builds on that foundation by utilizing data from the Midlife in the United States (MIDUS) study which included a total of 2,344 participants. The central research question is: Does workplace autonomy, workplace relatedness, and general competence, as conceptualized in Self-Determination Theory, influence employees' positive affect?

Autonomy was operationalized through "decision authority," relatedness through "coworker support," and competence through "persistence in goal striving" as each were composite scales that included several relevant questions/itens for each construct. Based on composite mean scores out of 5 for each one, the factors were re-categorized into three levels, low, medium, and high. Positive affect was measured by self-reported ratings of emotions such as cheerfulness, satisfaction, and feeling calm, peaceful, and full of life on a scale 1-10.

The study uses a quasi-experimental, unbalanced design using a three-way analysis of variance (ANOVA). Results from this study show significant main effects for autonomy relatedness ($p \leq 0.0001$), competence ($p < 0.001$), and autonomy ($p = 0.1036$), on positive effects, although no significant interactions were found. These findings show that autonomy, relatedness, and competence independently contribute to positive affect and each factor supports well-being without depending on the presence of the others. The results help inform employers and organization to prioritize fostering these elements in the workplace for increased employee positive affect, which might potentially impact employee productivity, morale, and satisfaction. Limitations and future research directions were discussed.

Literature Review

Prior investigations studying Self-Determination Theory (SDT), a well-established theory of motivation that has been widely applied across various domains such as health, sports, education, and the workplace (Ntoumanis, 2021). SDT emphasizes the importance of three basic psychological needs which are autonomy, competence, and relatedness, and they are essential for motivation and growth. The main theory behind SDT is that when people's psychological needs are met in their environment, their motivation becomes more autonomous. A study that was conducted by the National Institute of Health (NIH) where they aimed to investigate how the basic psychological needs impact task performance. Participants were tasked with folding origami puzzles, with some groups receiving support for competence and relatedness, and others not. The results showed that both competence and relatedness enhanced task performance, with competence having a stronger effect. In the second part of the study, participants played Boggle under varying conditions of reward and need support, with performance measured by the number of words found. Similar to the first study, competence support enhanced performance, and intrinsic motivation was a key mediator in the relationship between both competence and relatedness support and task outcomes. According to the NIH, “Both studies confirmed that the need for competence had the strongest positive influence on performance.” (Szulawski, 2021).

Since previous literature has shown relatively strong support for SDT, our focus wasn’t only to see if SDT factors impacts positive affect, but also if are any nuanced patterns that previous studies haven’t looked for or found. That said, we will be working from both a confirmatory data analysis (CDA) and exploratory data analysis framework (EDA).

Methodology

The present study utilizes data from the Midlife in the United States (MIDUS) study, specifically from its second wave (2004–2006). The MIDUS study aimed to investigate various aspects of health and well-being among middle-aged adults. Participants were selected using a nationally representative random-digit dialing (RDD) sampling technique, ensuring a diverse sample across the United States. To increase representation, older adults and men were oversampled through adjusted selection probabilities. Data collection was carried out through structured interviews and self-administered questionnaires. **Our statistical research question (SRQ) is: Does workplace autonomy, workplace relatedness, and general competence, as conceptualized in Self-Determination Theory, influence employees’ positive affect?**

To assess the influence of workplace autonomy, relatedness, and competence on employees’ positive affect, data cleaning and recoding steps were conducted. Autonomy was operationalized through the construct of “decision authority” variable in MIDUS) relatedness through the construct of ”coworker support” variable in MIDUS and competence through the construct of ”persistence in goal striving” variable in MIDUS where each measured as composite scales consisting of several relevant questions in MIDUS data set. Positive affect was operationalized by self-reported itens of positive emotions in a MIDUS validated construct of positive affect (B1SPOSAF in MIDUS), which including cheerfulness, satisfaction, and feelings of calm and peacefulness in a scale from 1-10. Please see Appendix A for detailed item descriptions.

All three variables—autonomy, relatedness, and competence—were recoded into categorical levels: Low (scores < 2.5), Medium ($2.5 \leq$ scores < 3.5), and High (scores ≥ 3.5). A contingency table confirmed that all 27 combinations of treatments (3 levels in autonomy $\times$ 3 levels in relatedness $\times$ 3 levels in competence) were represented in the data, with no zero cells for any treatment combinations. Since ANOVA prioritizes having all treatment combinations, this ensured we can proceed with our data.

This study uses a three-way ANOVA framework to examine the main effects and interaction effects of autonomy, relatedness, and competence on positive affect. At first, in our preliminary analysis, we had sex (male/female) as our block, where we would follow an partially incomplete block design (ANCOVA); however, an interaction between sex and the primary factor was detected. So, the blocking factor was removed to ensure satisfying model assumptions and validity. This study is also a quasi, experimental design. This is because because participants were not randomly assigned to the levels of the independent variables and are suveryed according to specific criteria, unlike experimental for the former and an observational study for the latter. Therefore, given the type of our study, we can’t make causal inferences. Also, we were looking into utilizing covariates as well for our 3-way ANOVA Model but found that many potential covariates we were interested in, such as financial status, were categorical variables in the MIDUS data. Thus, we omitted the incorporation of covariates in our study design.

We will be using an unusualness threshold of 0.12 because the findings of this study do not have high stakes or risks and due to our focus on finding new potential trends in the data. Data preparation and analysis were conducted in R, with outputs saved for reproducibility, including recoded datasets and contingency tables to document the full analytic process.

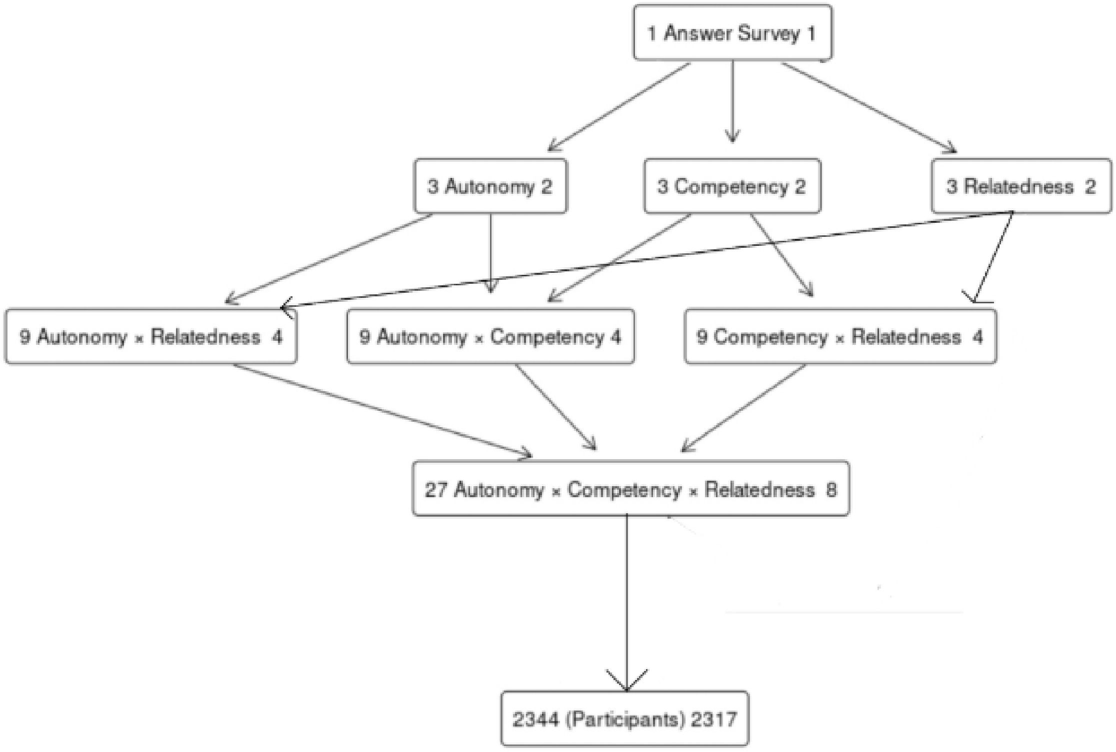

Figure 1: Hasse Diagram Displaying Study Design

The first node of the Hasse diagram in Figure 1 illustrates the primary action of answering the survey. The second node includes our three factors: autonomy, competence, and relatedness where the right side of the boxes show their respective levels: high, medium, and low for each. The third node shows that interactions between each two factors and the last node shows interactions between all the factors, totaling to 27 group combinations. Our response is positive affect which was measured from our measurement units, the participants. Since positive affect was measured directly through a self-report survey about positiveness, it's a primary response. We don't have experimental units in this study as this is a quasi, experimental study, so there is no manipulation of units.

With help of the Hasse diagram in Figure 1, we can also expand on why ANOVA is appropriate for the study. First, the response variable, positive affect, is a quantitative response, measured on a continuous scale. Second, the study includes three categorical factors—autonomy, competence, and relatedness—each with three levels (high, medium, low). Third, the study has sufficient degrees of freedom to estimate main effects and interactions, as shown by the total degrees of freedom (2,343) in the left side of fifth node and the degrees of freedom for residuals as seen in the right side of the fifth node (2,317).Also, the total variation in positive affect can be partitioned into the effects of the main factors, their interactions, and residual error as one can see in the Hasse diagram. Finally, the study uses an additive model, which includes main effects and interaction terms. Therefore, given all those things, ANOVA is an appropriate statistical tool to use for this study.

Data Exploration

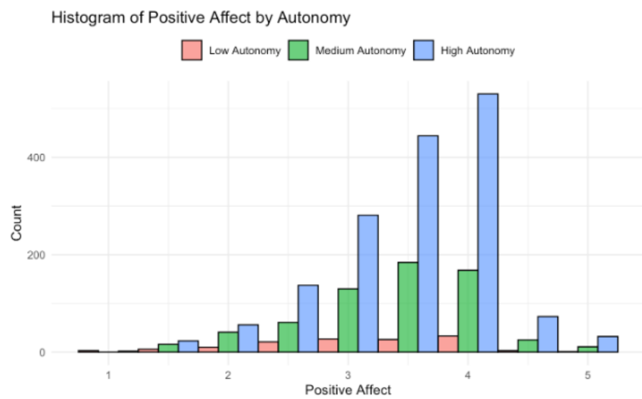

Figure 2: Histogram showing Positive Affect by Autonomy.

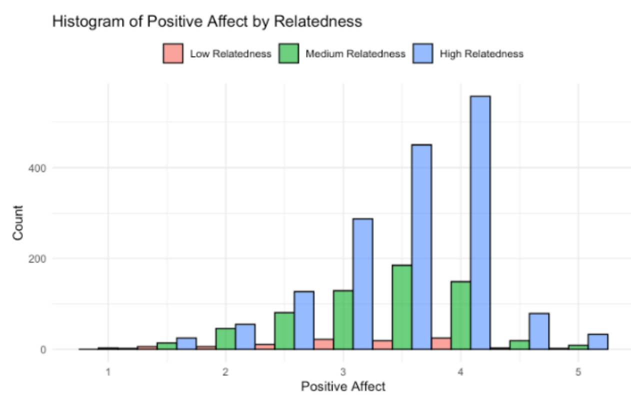

Figure 3: Histogram showing Positive Affect by Autonomy.

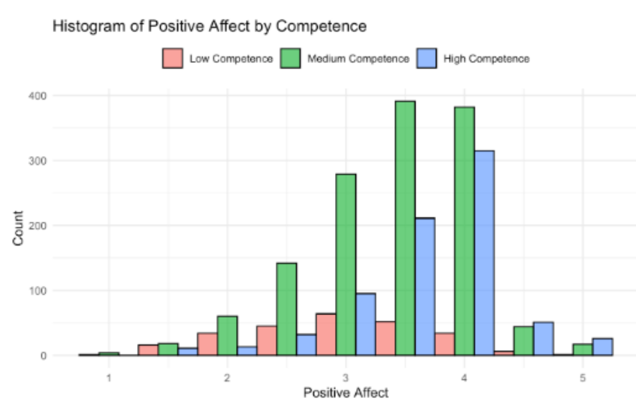

Figure 4: Histogram showing Positive Affect by Competence.

Data visualizations can provide us helpful insights about our data, so we will start with that. The histograms in Figure 2, Figure 3, and Figure 4 above show that high levels of relatedness and autonomy have the most overall observations, particularly concentrated at higher PA scores (PA = 4 and 5). In contrast, for competence, medium levels show the highest frequency of observations overall, with a strong peak at PA = 4. Low levels consistently have the fewest observations across all factors, clustering primarily around PA = 2 and 3, with minimal representation at higher scores. This emphasizes that while high relatedness and autonomy drive more frequent positive affect at higher levels, medium competence stands out for its overall prominence in observation frequency. In regards to SDT, this could suggests that medium and above levels of autonomy, relatedness, and competence may be associated with higher PA.

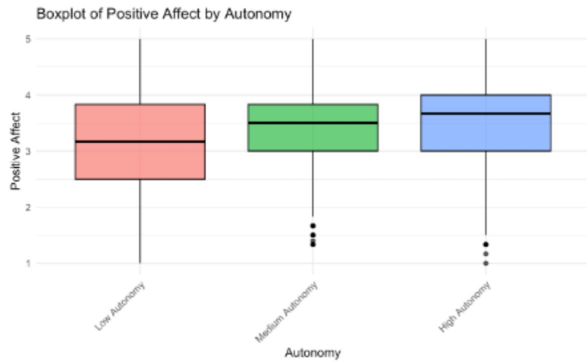

Figure 5: Box plot showing Positive Affect by Autonomy.

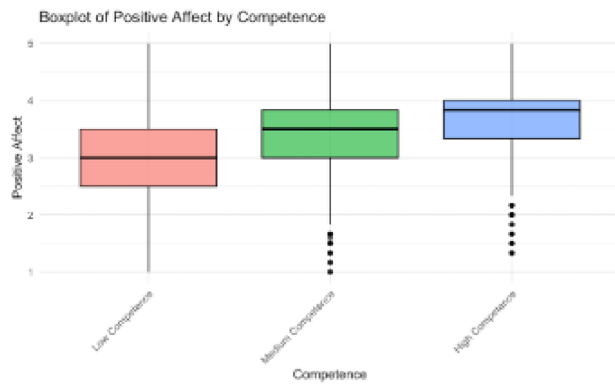

Figure 6: Box plot showing Positive Affect by Competence.

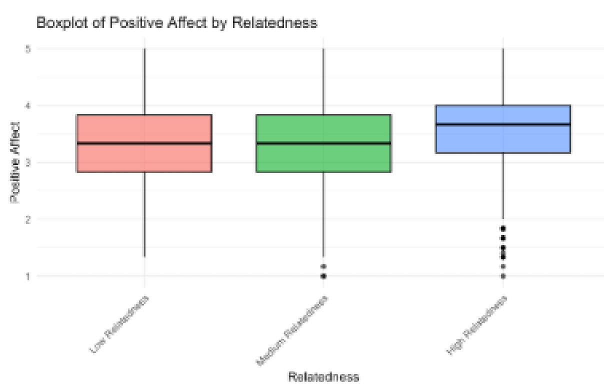

Figure 7: Box plot showing Positive Affect by Relatednes.

Box-plots in Figures 5, 6, and 7 are effective in helping us visualize Q1 (25th percentile of the data, median (50th percentile of the data) and Q3 (75 percentile of the data) as well as range and outliers. We can see that it shows a clear upward trend in positive affect (PA) scores as levels of relatedness, competence, and autonomy increase. Low levels of each factor have the lowest medians for competence and autonomy, with a higher median of for relatedness and narrower ranges. Medium levels show slight increases in medians for autonomy and competence with a lower median for relatedness. High levels across all three factors consistently have the highest medians with some observations reaching a PA score of 5. Also, high competence stands out with a stronger clustering of scores at the upper end suggesting it may have a great influence on PA. All that said, very few scores across all factors hit the maximum PA value, highlighting the rarity of extremely high PA even under optimal conditions. There tend to be outliers for positive affect between 1 and 2, specifically for medium and high levels of autonomy, competence, and relatedness, indicating variability in how individuals perceive or experience these factors. These outliers suggest that, while higher levels of autonomy, competence, and relatedness generally correspond to increased positive affect (PA), there may be other moderating or confounding variables influencing these relationships such as personality traits and external circumstances.

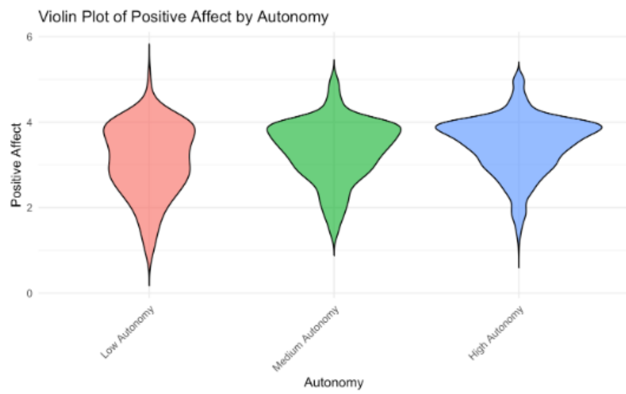

Figure 8: Violin Plot showing Positive Affect by Autonomy.

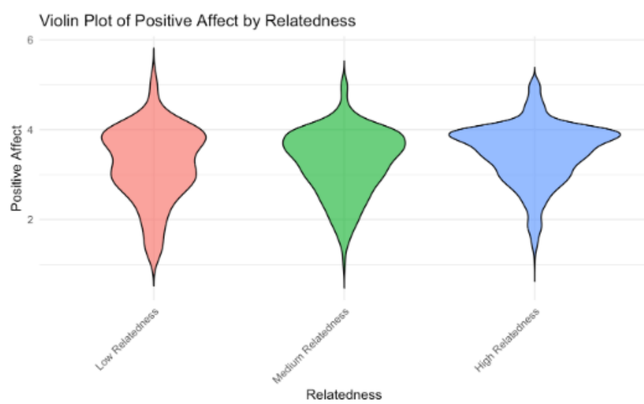

Figure 9: Violin plot showing Positive Affect by Relatedness.

Figure 10: Violin plot showing Positive Affect by Competence.

Looking at the violin plots in Figures 8, 9, and 10, we observe an upward trend in positive affect (PA) scores from low to medium to high levels across all three factors: autonomy, competence, and relatedness. The plots indicate that the lowest PA scores are consistently associated with the low levels of each factor. Medium levels of autonomy, competence, and relatedness also demonstrate effectiveness in supporting PA, often clustering around a PA score of 4. However, high levels of these factors exhibit a stronger influence, with scores showing a higher tendency toward elevated PA values. Also, low competence is associated with the highest concentration of scores around a PA value of 3, whereas low autonomy and low relatedness exhibit more observations near a PA score of 4. Interestingly, high levels across all three factors independently show only a limited number of observations reaching the maximum PA score of 5. Conversely, high competence demonstrates a greater frequency of observations at PA scores of 4 and 5 compared to the other factors. This suggests that competence may be a more sensitive factor in influencing PA.

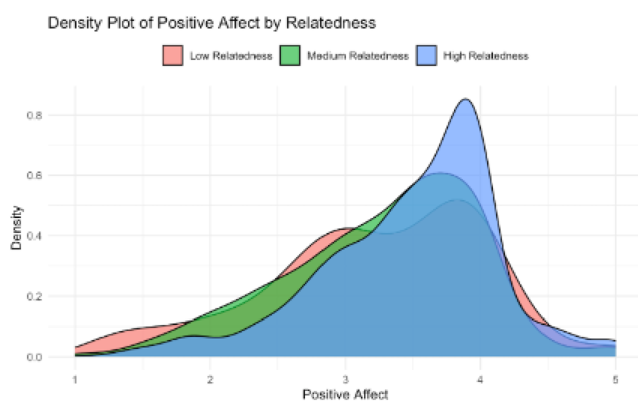

Figure 11: Density plot showing Positive Affect by Relatedness.

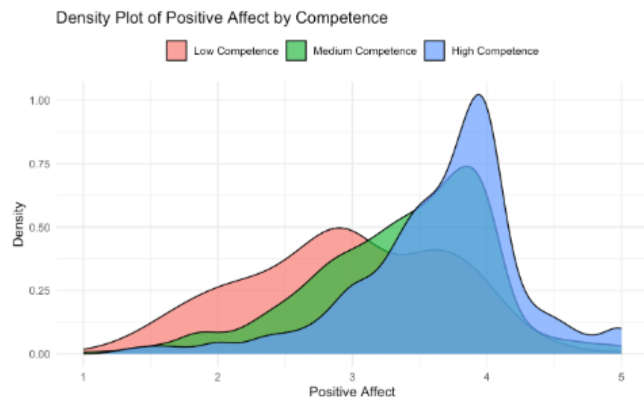

Figure 12: Density plot showing Positive Affect by Competence.

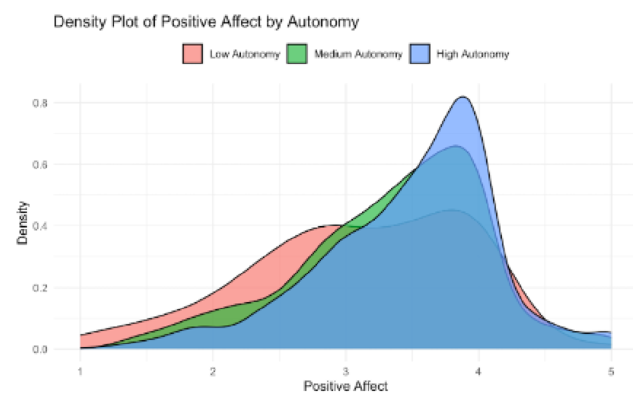

Figure 13: Density plot showing Positive Affect by Autonomy.

The density plots in figure 11, 12, and 13 reveal distinct patterns in Positive Affect (PA) across levels of autonomy, competence, and relatedness. High levels of all three factors consistently show sharp peaks at a PA score of 4. Medium levels of these factors exhibit broader distributions, reflecting greater variability in PA, although they still show some clustering around a PA score of 4. Low levels, on the other hand, are more scattered across lower PA scores, with low competence peaking at a PA score of 3. This suggests that low competency may have most negative impact on positive effect. On the other hand, low autonomy and low relatedness display smaller peaks at 4 but with wider spreads across lower scores, indicating a less consistent relationship with PA. These patterns, again, suggest that competence, may be most influential in maintaining higher levels of positive affect but also low levels of it has most impact on PA. Also, while medium levels can provide some benefit, high levels offer the more consistent PA.

Finally, after examining the outliers from our visualizations and given our large sample size, we think that it's better to not drop the outliers as we think they represent natural occurrences in the data.

Autonomy	Relatedness	Competence	n	Min	Q1	Median	Q3	Max	MAD	SAM	SASD	Sample Skew	
Low Autonomy	Low Relatedness	Low Competence	2	2.667	2.750	2.833	2.917	3.000	0.247	2.833	0.236	0.000	-2.750
Low Autonomy	Low Relatedness	Medium Competence	10	1.667	2.375	2.917	3.250	5.000	0.741	2.983	0.960	0.686	-0.496
Low Autonomy	Low Relatedness	High Competence	1	3.333	3.333	3.333	3.333	3.333	0.000	3.333		-0.270	
Low Autonomy	Medium Relatedness	Low Competence	20	1.000	2.292	2.833	3.083	4.000	0.741	2.742	0.773	-0.270	-0.499
Low Autonomy	Medium Relatedness	Medium Competence	31	1.000	2.500	2.833	3.500	4.167	0.741	2.930	0.708	-0.432	-0.031
Low Autonomy	Medium Relatedness	High Competence	7	2.000	2.500	3.500	3.500	4.000	0.741	3.071	0.757	-0.312	-1.765
Low Autonomy	High Relatedness	Low Competence	12	1.500	2.458	3.250	3.875	4.500	1.112	3.167	0.873	-0.278	-1.107
Low Autonomy	High Relatedness	Medium Competence	29	1.167	2.833	3.800	4.000	4.333	0.445	3.289	0.913	-0.981	-0.338
Low Autonomy	High Relatedness	High Competence	18	1.500	3.333	3.750	4.000	4.333	0.494	3.546	0.664	-1.508	2.343
Medium Autonomy	Low Relatedness	Low Competence	3	1.333	2.083	2.833	3.417	4.000	1.730	2.722	1.337	-0.083	-2.333
Medium Autonomy	Low Relatedness	Medium Competence	11	2.000	2.750	3.167	3.417	3.833	0.494	3.079	0.524	-0.431	-0.721
Medium Autonomy	Low Relatedness	High Competence	6	1.333	3.617	3.667	3.667	4.000	0.049	3.322	0.985	-1.294	-0.180
Medium Autonomy	Medium Relatedness	Low Competence	36	1.500	2.167	2.750	3.500	4.333	0.865	2.833	0.774	0.187	-1.110
Medium Autonomy	Medium Relatedness	Medium Competence	127	1.500	2.833	3.333	3.667	4.833	0.741	3.265	0.628	-0.475	-0.223
Medium Autonomy	Medium Relatedness	High Competence	44	1.500	3.167	3.500	3.833	4.833	0.494	3.433	0.652	-0.854	1.064
Medium Autonomy	High Relatedness	Low Competence	49	1.333	2.333	3.000	3.667	5.000	0.988	2.961	0.866	0.076	-0.792
Medium Autonomy	High Relatedness	Medium Competence	242	1.667	3.000	3.500	3.833	5.000	0.494	3.404	0.649	-0.441	0.190
Medium Autonomy	High Relatedness	High Competence	118	1.500	3.333	3.750	4.000	5.000	0.494	3.644	0.621	-0.702	1.576
High Autonomy	Low Relatedness	Low Competence	9	1.333	2.000	2.667	3.000	3.667	0.494	2.519	0.733	-0.183	-1.299
High Autonomy	Low Relatedness	Medium Competence	30	1.833	3.000	3.333	3.833	5.000	0.741	3.328	0.653	0.027	0.154
High Autonomy	Low Relatedness	High Competence	22	1.333	3.708	4.000	4.000	4.500	0.247	3.652	0.810	-1.585	1.373
High Autonomy	Medium Relatedness	Low Competence	44	1.667	2.458	2.833	3.333	4.167	0.741	2.837	0.663	0.129	-0.905
High Autonomy	Medium Relatedness	Medium Competence	215	1.167	3.000	3.333	3.833	5.000	0.741	3.319	0.699	-0.554	0.287
High Autonomy	Medium Relatedness	High Competence	111	1.667	3.500	3.667	4.000	5.000	0.494	3.652	0.599	-0.756	1.762
High Autonomy	High Relatedness	Low Competence	78	1.500	2.833	3.167	3.667	4.333	0.741	3.159	0.652	-0.567	-0.307
High Autonomy	High Relatedness	Medium Competence	642	1.000	3.000	3.500	3.833	5.000	0.494	3.435	0.623	-0.688	0.727
High Autonomy	High Relatedness	High Competence	427	1.333	3.333	3.833	4.000	5.000	0.494	3.699	0.589	-0.614	1.359

Table 1: Summary Statistics for Positive Affect by Autonomy, Relatedness, and Competence

We will be utilizing a summary statistics table that show all our twenty-seven group combinations as it can also help us better understand the distribution of the data. In Table 1, we can see that each group has different number of participants, showing an unbalanced design. What was specially noticeable is the low competence, low relatedness, and low autonomy with n = 1, and the high competence, high low autonomy, low relatedness group with only n = 2. On the other hand, group combinations with more of the high and medium levels has more participants overall (e.g., n = 427 for high autonomy, high relatedness, and high competence). This means that the unbalanced design could reduce the statistical power to detect significant effects for groups with very small sample sizes (e.g., n = 1 or 2)

When examining the summary statistics for positive affect (PA) scores across autonomy, relatedness, and competence, several key trends emerge. The median, which represents the middle value of the data, shows that competence has the highest median score of 3.6, followed by autonomy and relatedness, both at 3.5, suggesting that competence tends to produce higher PA scores overall. The sample maximum reflects the highest scores achieved, with the high competence group achieving the highest values, followed by autonomy and relatedness. The first quartile (Q1), which represents the value below which 25 % of the data falls, indicates that relatedness has the highest Q1 value, suggesting a distribution skewed toward higher PA scores, while autonomy and competence show somewhat similar Q1 values but with more variation.

The Sample Arithmetic Mean (SAM), representing the average of the data, shows that competence has the highest mean score at 3.5, followed by relatedness at 3.44 and autonomy at 3.33. The Mean Absolute Deviation (MAD), which measures the average absolute deviation from the mean, shows that competence has the highest MAD, indicating greater variability around the mean, whereas relatedness and autonomy have lower MADs, suggesting more consistency in their scores. The Sample Standard Deviation (SASD), which measures the spread of the data around the mean, confirms that competence has the highest variability, followed by autonomy, while relatedness has the lowest variability, indicating more stability in its scores. The Sample Skewness measures the asymmetry of the data distribution. Relatedness and competence both show mild negative skewness, suggesting a tendency for higher PA scores, while autonomy has a slight positive skew, reflecting a tendency toward lower scores. This is also supported by the median and trimmed mean, where relatedness and competence are skewed toward higher values.

Next, the Sample Excess Kurtosis, which measures the "tailedness" of the distribution, indicates relatively flat distributions for all three factors, with no significant outliers in any of the PA scores. Finally, the Interquartile Range (IQR), measures the range between the first and third quartiles, shows that the middle 50 % of the data for relatedness is more concentrated, with a narrower range compared to the broader ranges observed for autonomy and competence, especially in the low competence group.

Overall, inasfar as observing the summary statistics, it appears that higher levels of autonomy, relatedness, and competence are associated with stronger and more consistent positive affect, while lower levels are linked to increased variability and lower median scores.

Assessing Assumptions

To have valid results using an ANOVA model, we need to first assess if our data satisfies the assumptions of the model that falls under the F-distribution. These are Gaussian distribution, homoscedasticity, and independence of observations.

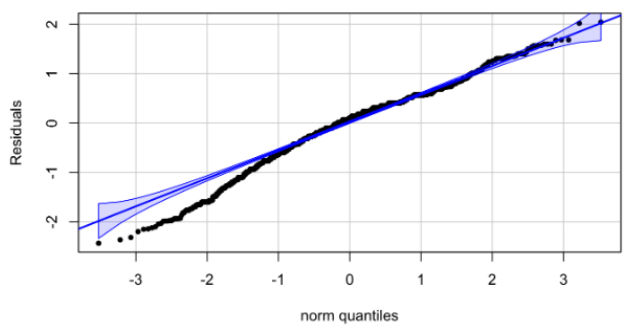

Figure 14: QQ Plot

We utilized a QQ plot to help us assess gaussian distribution assumption of ANOVA. As shown in Figure 14, many points fall outside the 90% envelope, which makes us concerned about whether the data fully follows a Gaussian distribution. However, the visualization is also not very clear due to the overwhelming number of observations. To further investigate, we calculated the sample skewness (-0.5654) and sample kurtosis (0.6479). These values suggest a slight left skewness and marginally heavier tails than expected under a Gaussian distribution. While these deviations are notable, they are not extreme and fall within acceptable ranges for most statistical analyses. Therefore, we proceed under the assumption that the residuals sufficiently meet the Gaussian distribution assumption, though we will interpret results with caution.

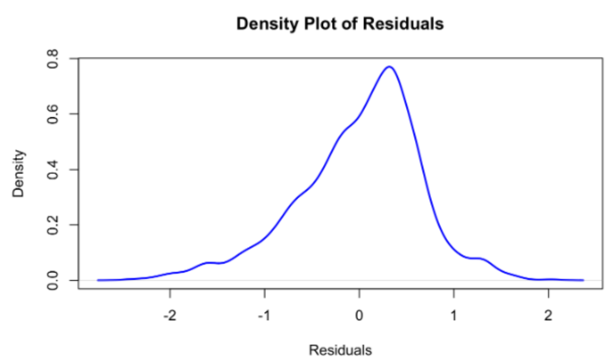

Figure 15: Denity plot of Residuals

To further investigate this, we conducted a density plot for the residuals which shows that residuals are concentrated near zero as well as a relatively symmetric and unimodal distribution. This further supports that the residuals approximate a Gaussian distribution. Now, we feel more assured to proceed with using our data with our ANOVA model.

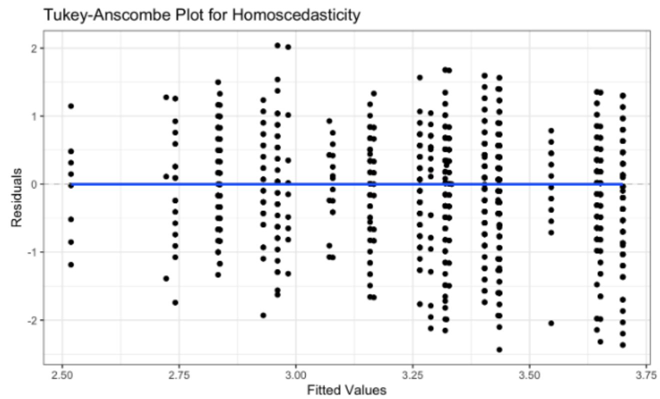

Figure 16: Tukey-Anscombe Plot

The Tukey-Anscombe plot helps assess for homoscedasticity assumption which investigates whether the residuals have constant variance across the range of fitted values. In this plot, the residuals appear to be evenly distributed around the reference line, with no strong patterns suggesting a violation of this assumption. We also have a straight reference light which makes us think of it as a good sign. However, there is minor clustering of points at certain values, but clustering could potentially be explained by the influence of the three factors in the data. We would say that the homoscedasticity assumption is satisfied.

As for the independence of observations assumption of ANOVA, unfortunately, we do not have the measurement order to assess for it, so we can only make use of the study design. We know that the study utilized Random Digit Dialing, which is a sampling technique where participants are selected by generating phone numbers randomly. Due to this, we deem independence of observations assumption as satisfied.

We believe that the assumption of the model are mostly satisfied, with only minor deviations in our gaussian distribution assumption. Now, we can proceed with the analysis of the results from the three-way ANOVA model.

Results

To explore the research question, we will utilize a hypothesis test. The null hypothesis will be that there are no main effects or interaction effects among competence, relatedness, and autonomy on positive affect score. Our alternative hypothesis will be that there is at least one significant main effect or interaction effect on positive affect score. We can our hypotheses these mathematically as:

$$H_0 : \mu_{Competence} = \mu_{Relatedness} = \mu Autonomy$$

$$H_1 : \mu_{Competence} \neq \mu_{Relatedness} \neq \mu Autonomy$$

ANOVA Table

Source	SS	df	MS	F	p-value	Partial η^2	Partial ω^2	Partial ε^2
competence	12.550	2	6.275	14.793	< 0.0001	0.013	0.012	0.012
relatedness	10.127	2	5.064	11.937	< 0.0001	0.010	0.009	0.009
autonomy	1.925	2	0.963	2.269	0.1036	0.002	0.001	0.001
competence:relatedness	0.376	4	0.094	0.221	0.9266	0.000	0.000	0.000
competence:autonomy	1.660	4	0.415	0.978	0.4180	0.002	0.002	0.002
relatedness:autonomy	1.453	4	0.363	0.856	0.4896	0.001	0.000	0.000
competence:relatedness:autonomy	1.792	8	0.224	0.528	0.8361	0.002	0.000	0.000
Residuals	982.839	2,317	0.424					

Table 2: ANOVA Omnibus Test

We used the ANOVA omni-bus parametric shortcut test, as shown in Table 2, to answer our research question if autonomy, relatedness, and competence influences positive affect. This means that our sampling distribution is developed under a parametric shortcut, specifically a F-distribution. A three-way ANOVA test was conducted to examine the effect of the levels: high, medium, and low of each competence, relatedness, and autonomy on positive effect.

In Table 2, Starting with competence, its p-value is less than 0.0001, which is well below the Unusualness Threshold (UT) of 12%. The p-value here reflects the probability of observing an F-statistic as large as 14.793, or larger, if the null hypothesis was true. In other words, this also means that competence accounts for about 14.8 times more variation than the residuals and explains roughly 1.3% of the total variance (partial eta squared = 0.013). While the effect size is modest, it warrants our attention. Relatedness also has a p-value of < 0.0001, showing strong statistical significance. With $F = 11.937$, $p < 0.0001$, this means that relatedness accounts for approximately 12 times more variation than the residuals and explains about 1.3% (as indicated by partial eta squared of 0.010) of the total variance in the dependent variable. Autonomy, with a p-value of 0.1036, also falls below our chosen UT of 12%. A p-value of 0.1036 suggests there's about a 10.4% chance of observing an F-statistic as large as 2.269, or larger, under our null hypothesis mode. Also, $F = 2.269$, $P < 0.1036$, means that competence accounts for about 2 times more variation than the residuals. It also only accounts for 0.2% of the total variance (as indicted by partial eta squared = 0.002). While this result is statistically significant, its practical importance appears quite limited, especially compared to the other factors. Therefore, we will reject the null hypothesis that is under our model in regards to displaying main effects on positive affect.

As for the interactions, none of the two-way and three-way interactions terms were statistically significant. The competence $\times$ relatedness interaction has a p-value of 0.9266, which is far above our UT of 0.12. Similar results were found for competence $\times$ autonomy, relatedness $\times$ autonomy, and the three-way interaction (competency x autonomy x relatedness). Thus, for all interaction effects, we will fail to reject the null hypothesis that is under our model.

Finally, an interesting part of the table is our Sum of Squares (SS). It shows us the variability explained by these factors in the dependent variable. We can see that the SS of the *residuals* show most of the variability (982.839) that remains unaccounted for by the model. The residual sum of squares may have things that influenced it by measurement error, individual differences, or variables that influence positive affect that we didn't account for.

Overall, the ANOVA results suggest that all factors have significant impact on positive affect; however, relatedness and autonomy show more practical significance as indicated by their effect size. This may mean that improving feelings of competence and relatedness may be more impactful and worthwhile for employers than focusing on autonomy.

Table 3: Point Estimates

Category	Term	Estimate
Grand Mean	Grand Mean	3.19
9***Main Effects**	Low Competence	-0.33
	Medium Competence	0.03

Category	Term	Estimate
	High Competence	0.29
	Low Relatedness	-0.11
	Medium Relatedness	-0.07
	High Relatedness	0.18
	Low Autonomy	-0.09
	Medium Autonomy	-0.01
	High Autonomy	0.10
27***Two-Way Interactions**	Low Competence x Low Relatedness	-0.07
	Medium Competence x Low Relatedness	0.01
	High Competence x Low Relatedness	0.06
	Low Competence x Medium Relatedness	0.01
	Medium Competence x Medium Relatedness	0.02
	High Competence x Medium Relatedness	-0.03
	Low Competence x High Relatedness	0.06
	Medium Competence x High Relatedness	-0.03
	High Competence x High Relatedness	-0.03
	Low Competence x Low Autonomy	0.14
	Medium Competence x Low Autonomy	-0.07
	High Competence x Low Autonomy	-0.08
	Low Competence x Medium Autonomy	-0.02
	Medium Competence x Medium Autonomy	0.03
	High Competence x Medium Autonomy	-0.01
	Low Competence x High Autonomy	-0.12
	Medium Competence x High Autonomy	0.04
	High Competence x High Autonomy	0.09
	Low Relatedness x Low Autonomy	0.06
	Medium Relatedness x Low Autonomy	-0.11
	High Relatedness x Low Autonomy	0.06
	Low Relatedness x Medium Autonomy	-0.04
	Medium Relatedness x Medium Autonomy	0.06
	High Relatedness x Medium Autonomy	-0.02
	Low Relatedness x High Autonomy	-0.02
	Medium Relatedness x High Autonomy	0.05
	High Relatedness x High Autonomy	-0.03
27***Three-Way Interactions**	Low Competence x Low Relatedness x Low Autonomy	0.04
	Medium Competence x Low Relatedness x Low Autonomy	-0.04
	High Competence x Low Relatedness x Low Autonomy	0.01
	Low Competence x Medium Relatedness x Low Autonomy	0.00
	Medium Competence x Medium Relatedness x Low Autonomy	0.03
	High Competence x Medium Relatedness x Low Autonomy	-0.03
	Low Competence x High Relatedness x Low Autonomy	-0.04
	Medium Competence x High Relatedness x Low Autonomy	0.01
	High Competence x High Relatedness x Low Autonomy	0.02
	Low Competence x Low Relatedness x Medium Autonomy	0.09
	Medium Competence x Low Relatedness x Medium Autonomy	-0.04
	High Competence x Low Relatedness x Medium Autonomy	-0.06
	Low Competence x Medium Relatedness x Medium Autonomy	-0.01
	Medium Competence x Medium Relatedness x Medium Autonomy	0.01
	High Competence x Medium Relatedness x Medium Autonomy	0.00
	Low Competence x High Relatedness x Medium Autonomy	-0.09
	Medium Competence x High Relatedness x Medium Autonomy	0.03
	High Competence x High Relatedness x Medium Autonomy	0.06
	Low Competence x Low Relatedness x High Autonomy	-0.13

Category	Term	Estimate
	Medium Competence x Low Relatedness x High Autonomy	0.08
	High Competence x Low Relatedness x High Autonomy	0.05
	Low Competence x Medium Relatedness x High Autonomy	0.01
	Medium Competence x Medium Relatedness x High Autonomy	-0.04
	High Competence x Medium Relatedness x High Autonomy	0.03
	Low Competence x High Relatedness x High Autonomy	0.12
	Medium Competence x High Relatedness x High Autonomy	-0.04
	High Competence x High Relatedness x High Autonomy	-0.08

We calculated the point estimates, as shown in table 3, to better understand the direction and magnitude of changes in positive affect in relation to our factors, competence, relatedness, and autonomy, when relation to its baseline, the grand mean. The grand mean ($\mu = 3.19$) represents the average positive affect score across all participants, serving as a baseline for comparison. Participants with high competence exhibited an increase of +0.29 units in positive affect compared to this grand mean. This indicates that, on average, individuals perceiving high competence experience a positive affect score of 3.48, which is 0.29 units above the baseline.

In contrast, those with low competence showed a decrease of -0.33 units from the grand mean, resulting in an average positive affect score of 2.86. Similarly, participants with high relatedness reported a +0.18 unit increase in positive affect, averaging a score of 3.37, while those with low relatedness experienced a -0.11 unit decrease, averaging 3.08. Also, high autonomy was associated with a +0.10 unit increase (average score of 3.29), and low autonomy with a -0.09 unit decrease (average score of 3.10). These findings suggest that higher levels of relatedness and autonomy are linked to modest increases in positive affect.

Although the interaction terms were not statistically significant, the point estimates offer exploratory insights into potential combined effects. For instance, the estimate for High Competence × Medium Relatedness (-0.03) suggests a slight reduction in positive affect compared to the additive effects of high competence and medium relatedness alone. Similarly, Low Competence × High Relatedness × High Autonomy (+0.12) indicates a small increase in positive affect for this combination. However, these estimates should be interpreted very cautiously as we haven't observed significant 3-way interactions in our ANOVA results.

Again, the results from the point estimates suggest that competence has the most substantial impact on positive affect, followed by relatedness, with autonomy contributing to a lesser extent. It also appears that the factors are better approached in a separate, additive way rather than interdependently. This may also mean that lower levels of competence may impact positive affect more severely so than relatedness and autonomy, warranting organizations to prioritize it as a construct to target.

Table 4: Pairwise Comparison for Relatedness

Pairwise Comparison	**Difference**	**SE**	**DF**	**t**	**p-value**
Low Relatedness - Medium Relatedness	-0.0346	0.1189	2317	-0.2909	0.7712
Low Relatedness - High Relatedness	-0.2813	0.1168	2317	-2.4093	0.0241
Medium Relatedness - High Relatedness	-0.2468	0.0533	2317	-4.6274	< 0.0001

Table 5: Pairwise Comparison for Autonomy

Pairwise Comparison	**Difference**	**SE**	**DF**	**t**	**p-value**
Low Autonomy - Medium Autonomy	-0.0853	0.1185	2317	-0.7201	0.4715
Low Autonomy - High Autonomy	-0.1894	0.1033	2317	-1.7482	0.2025
Medium Autonomy - High Autonomy	-0.1041	0.0696	2317	-1.4952	0.2025

Table 6: Pairwise Comparison for Competence

Pairwise Comparison	Difference	SE	DF	t	p-value
Low Competence - Medium Competence	-0.3622	0.0878	2317	-4.1275	0.0001
Low Competence - High Competence	-0.6201	0.1170	2317	-5.2991	< 0.0001
Medium Competence - High Competence	-0.2578	0.0961	2317	-2.6839	0.0073

We used pairwise comparisons to more specifically look at the comparison of levels between each factor. For our pairwise comparisons, as can be seen in Table 4, 5, and 6, we used the False Discovery Rate (FDR) adjustment to address the multiple comparisons problem, which arises when conducting multiple pairwise tests and increases the likelihood of false positives. The FDR method accounts for this risk by adjusting p-values to maintain our rate of =0.12. This flexible method is suitable for our EDA-based framework since we are focused on finding new potential patterns in relation to SDT over being correct almost all the time.

As can be seen in table 6, regarding Competence, significant differences were observed at every level. Low Competence ratings were significantly lower than both Medium Competence (D = 0.362, SE = 0.088, p < 0.001) and High Competence (D = 0.620, p < 0.001). Medium Competence ratings were also significantly lower than High Competence (Difference = 0.258, p = 0.007). This reinforces that perceptions of Competence have a linear impact on Positive Affect, with higher Competence levels showcasing greater Positive Affect.

Relatedness exhibited a more selective pattern. While Low and Medium Relatedness ratings did not differ significantly (D = 0.035, SE = 0.119, p = 0.7712), High Relatedness ratings were significantly higher than both Medium Relatedness (D = 0.247, p < 0.001) and Low Relatedness (D = 0.281, SE = 0.117, p = 0.0241). This indicates that High Relatedness uniquely enhances Positive Affect, whereas Low and Medium Relatedness exert a similar, more limited impact.

In contrast to the previous two, Autonomy showed no significant differences across levels. Comparisons between Low and Medium Autonomy (D = 0.085, SE = 0.119, p = 0.4715), Low and High Autonomy (D = 0.189, p = 0.2025), and Medium and High Autonomy (D = 0.104, p = 0.2025) all failed to reach significance. These results suggest that perceptions of Autonomy maintain a consistent and stable relationship with Positive Affect, regardless of level.

All in all, the results seems to be consistent to what we noticed from both the ANOVA test and point estimates. The pairwise comparisons suggest that PA is most strongly influenced by all levels of competence and high relatedness. Based on these findings, it might be beneficial for interventions aiming to enhance Positive Affect to prioritize fostering perceptions of Competence first and High Relatedness as second. The role of Autonomy seems to be investigated further.

Contrast	Difference	SE	DF	t Statistic	p-value	Cohen's d	Prob. of Superiority
High & Medium Autonomy vs. Low Autonomy	0.1374	0.1081	2317	1.2712	0.2038	0.0528	0.5211
High & Medium Competence vs. Low Competence	0.4911	0.0916	2317	5.3621	0	0.2228	0.5882
High & Medium Relatedness vs. Low Relatedness	0.158	0.1148	2317	1.376	0.1689	0.0572	0.5228

Table 7: Contrast Results for Autonomy, Competence, and Relatedness Levels

We specifically wanted to see how higher than low levels (high and medium) of each construct compare to low levels, to see if low levels of each factors present starkly different positive from the higher ones. The contrasts, adjusted using the False Discovery Rate (FDR) method to control the proportion of false positives, provide insights into the effects of competence, autonomy, and relatedness on positive affect. The FDR adjustment was chosen as a less conservative alternative to Bonferroni as we want to balance the need to detect potential effects while maintaining control over Type I errors in this exploratory analysis. The specific contrast vector used was $c(1, 0.5, 0.5)$ which compares the low group (-1) against the combined average of the high (0.5) and medium (0.5) groups.

For competence, the contrast comparing high and medium levels against low was statistically significant ($p < 0.001$) with a mean difference of 0.4911 units. The probability of superiority (0.5882) suggests that a randomly chosen individual from the high or medium competence group is 58.8% more likely to report a higher positive affect score than one from the low group. These results highlight the importance of fostering competence as a important driver of PA in workplace settings.

For autonomy ($p = 0.2038$) and relatedness (p = 0.1689) contrasts between medium and high vs. low, both were not statistically significant. The mean differences for autonomy and relatedness were 0.1374 and 0.158, respectively. Although, there probabilities of superiority are relatively high, both close to 50%. These small differences and non-significant p-values suggest weaker or negligible associations with positive affect for these factors.

These findings suggest that competence has the strongest difference on positive affect when it's high and medium vs. low, while autonomy and relatedness play less significant roles. Workplace interventions should prioritize building competence through goal-setting, skill development, and opportunities for mastery. Further research is needed to explore the nuanced contributions of autonomy and relatedness across diverse environments.

Competence Level	**Marginal Mean**	**SE**	**df**	**Lower Bound**	**Upper Bound**
Low Competence	2.864	0.078	2317	2.703	3.024
Medium Competence	3.226	0.040	2317	3.143	3.308
High Competence	3.484	0.087	2317	3.304	3.663

Table 8: Marginal Means for Competence Levels

Relatedness Level	**Marginal Mean**	**SE**	**df**	**Lower Bound**	**Upper Bound**
Low Relatedness	3.086	0.112	2317	2.856	3.315
Medium Relatedness	3.120	0.041	2317	3.036	3.204
High Relatedness	3.367	0.034	2317	3.297	3.437

Table 9: Marginal Means for Relatedness Levels

Autonomy Level	**Marginal Mean**	**SE**	**df**	**Lower Bound**	**Upper Bound**
Low Autonomy	3.099	0.102	2317	2.889	3.310
Medium Autonomy	3.185	0.060	2317	3.062	3.308
High Autonomy	3.289	0.036	2317	3.216	3.362

Table 10: Marginal Means for Autonomy Levels

We incorporated marginal means, as seen in table 8, 9, and 10, as part of our post-hoc analyses as it helps us account for external factors influencing positive affect apart from the factor itself. This helps us make have better understanding of the differences between the factors.

For competence, participants in the high competence group had a marginal mean score of 3.484, compared to 2.86 for the low competence group. This reflects an increase of 0.62 points in positive affect, with high competence participants demonstrating approximately 3.48 times as much positive affect as their level of competence suggests. We can also say that this specific MIDUS sample suggests that when used along our chosen 88% confidence method, the positive affect of participants with high competence might be between 3.30 and 3.66.

The marginal means also reflect rates of change in positive affect across levels of each factor. For example, for medium relatedness, the observed rate of change indicates a 0.25-point increase in positive affect for each unit increase in relatedness. In comparison, autonomy demonstrates a smaller rate of change, with only a 0.10-point increase in positive affect observed between its low and high levels.

More generally, the trend indicates that competence consistently has the strongest and most linear effect on positive affect, while relatedness more so at higher levels (between medium and high), and autonomy demonstrates a minimal increase across levels. In context, these findings highlight the potential for improving well-being, job satisfaction, and productivity by particularly targeting higher levels of competence and relatedness in the workplace.

Discussion and Conclusion

Back to our SRQ: Does workplace autonomy, workplace relatedness, and general competence, as conceptualized in Self-Determination Theory, influence employees' positive affect? This study examined whether workplace factors—autonomy, relatedness, and competence—independently and interactively influence positive affect as conceptualized by SDT. Competence and relatedness emerged as the strongest predictors, explaining 1.3% and 1.0% of the variance in positive affect, respectively, while autonomy, though statistically significant, accounted for only 0.2%, indicating a smaller practical effect.

The planned contrast analysis revealed significant differences for competence and relatedness between high-/medium and low levels ($p < 0.001$), suggesting a linear relationship with positive affect. For autonomy, the planned contrasts did not indicate significant differences across levels ($t = -2.122$, $p = 0.034$), reflecting a limited and less consistent impact on positive affect compared to the other factors. Pairwise comparisons supported these findings, with high competence and high relatedness consistently associated with significantly greater positive affect, while autonomy showed no significant differences across levels, reflecting its more uniform influence. Marginal means showed that high levels of competence and relatedness led to the highest positive affect scores, with clear separation from lower levels. Autonomy, however, exhibited smaller and less distinct increases. The findings suggest that general competence and workplace relatedness play critical roles in fostering positive affect while workplace autonomy seems to play a lesser role.

The findings of this report help inform organizations and employers in prioritizing building competence as a first priority and relatedness as a second priority. This can be done through training programs and team-building activities. Since we did not find significant 2-way and 3-way interactions across all factors, this also means that organizations may work on targeting each construct separately as they do not appear to be interdependent on one other (i.e., no significant interactions). Also, while autonomy suggests a lower practical significance, it is a core component of SDT and past research has shown its effectiveness. Therefore, this warrants further investigation in terms of its effect on positive emotions.

There are a couple of limitations in this study. First, we saw competence impacting affect most pronouncedly across different tests, but its construct was developed as a person's general feelings of competence, not specifically in regard to the workplace. This is different from the constructs of relatedness and autonomy, where the questions were very specific to workplace factors (see Appendix A). This might be one reason why competence consistently showed better results. A second important limitation is that our unbalanced design of unequal group sizes may have reduced statistical power for smaller groups (groups where $n < 5$), reducing the reliability of comparisons. Third, the geographical location of the participants, being in the U.S., limits the generalizability of the study to other workplace settings. Last but not least, the study has a couple of potential confounding variables. Confounding variables are variables that impact both the factors and our response that it becomes hard to parse them out. In our study, this may include mental health problems, workplace stress, and/or personality trait that may affect positive affect and our factors simultaneously. Future designs can include them as covariates to account for their impact.

Future research, including national surveys, should focus more on developing and gathering information on workplace-specific constructs of competence as opposed to general feelings of competence. In addition, future studies can look onto the the longitudinal, long-term effects of these factors on positive affect rather than at one time point.

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Appendix A: Item Details for Measuring Constructs

Variables

Relatedness (Coworker Support) [B1SJCCS]

Scale Name (MIDUS 1): A1SJCCS Options: All of the time, Most of the time, Some of the time, Rarely, Never Items:

- "How often do you get help and support from your coworkers?"
- "How often are your coworkers willing to listen to your work-related problems?"

Competence (Primary Control/Persistence in Goal Striving) [B1SPERSI]

Competence (Primary Control/Persistence in Goal Striving) [B1SPERSI] Scale Name (MIDUS 1): A1SPERSIS Options: A lot, Some, A little, Not at all Items:

- "When things don't go according to my plans, my motto is, 'Where there's a will, there's a way'."
- "When faced with a bad situation, I do what I can to change it for the better."
- "Even when I feel I have too much to do, I find a way to get it all done."
- "When I encounter problems, I don't give up until I solve them."
- "I rarely give up on something I am doing, even when things get tough."

Positive Affect [B1SPOSAF]

Scale Name (MIDUS 1): A1SPOSAF Options: All of the time, Most of the time, Some of the time, Rarely, Never Items: (During the past 30 days, how much of the time did you feel...)

- "in good spirits?"
- "extremely happy?"
- "calm and peaceful?"
- "satisfied?"
- "full of life?"
- "cheerful?"

Appendix B: Code

This section contains the R code used for data analysis, visualization, and hypothesis testing in this study. Each code block is labeled and documented for clarity. Used Dr. Hatfield's GitHub `hatfield2024stat461` Repository as reference and used some guidance from ChatGPT `https://chat.openai.com/`, although it was then was edited and adapted to fit the specific needs of this project.

```



```{r}
#cleaning data

# Load necessary libraries
library(dplyr)

# Load the .rda file and assign the dataset
load("/Users/randkhunaizi/Downloads/STAT_461_FINAL_PROJECT/Data/Raw Data/04652-0001-Data.rda")
data <- da04652.0001


# Clean data
data_cleaned <- data %>%
  # Select the unique participant identifier (M2ID) and desired columns
  select(
    participant_id = M2ID,       # Rename M2ID to participant_id
    autonomy = B1SJCDA,          # Rename B1SJCDA to autonomy
    relatedness = B1SJCCS,       # Rename B1SJCCS to relatedness
    competence = B1SPERSI,       # Rename B1SPERSI to competence
    positive_affect = B1SPOSAF  # Rename B1SPOSAF to positive_affect
  ) %>%
  # Remove rows where any of the selected columns (except participant_id) have NA
  filter(
    !is.na(autonomy) &
      !is.na(relatedness) &
      !is.na(competence) &
      !is.na(positive_affect)
  ) %>%
  # Modify values for specific columns
  mutate(
    relatedness = relatedness / 2,
    autonomy = autonomy / 6
  )

# see cleaned data
cat("\nPreview of the cleaned data:\n")
print(head(data_cleaned))

# Save the cleaned data to a CSV file
output_dir <- "/Users/randkhunaizi/Downloads/STAT GP4 DATA/"
if (!dir.exists(output_dir)) {
  dir.create(output_dir, recursive = TRUE)
  cat("Created output directory:", output_dir, "\n")
}

output_path <- file.path(output_dir, "cleaned_data.csv")
write.csv(data_cleaned, output_path, row.names = FALSE)
cat("\nCleaned data saved to:", output_path, "\n")

# structure of the cleaned data
cat("\nFinal structure of the cleaned data:\n")
str(data_cleaned)


## recode data,

data_cleaned <- read_csv("/Users/randkhunaizi/Downloads/STAT_461_FINAL_PROJECT/Data/updated data
    as of 18:12:2024/cleaned_data.csv")

# Check and convert relatedness to numeric if needed
```
```

```r
data_cleaned <- data_cleaned %>%
  mutate(
    relatedness = as.numeric(as.character(relatedness)),
    autonomy = as.numeric(as.character(autonomy)),
    competence = as.numeric(as.character(competence))
  )

# Recode autonomy, relatedness, and competence directly
data_cleaned <- data_cleaned %>%
  mutate(
    autonomy = case_when(
      autonomy >= 1 & autonomy < 2.5 ~ "Low Autonomy",
      autonomy >= 2.5 & autonomy < 3.5 ~ "Medium Autonomy",
      autonomy >= 3.5 & autonomy <= 5 ~ "High Autonomy",
      TRUE ~ NA_character_
    ),
    relatedness = case_when(
      relatedness >= 1 & relatedness < 2.5 ~ "Low Relatedness",
      relatedness >= 2.5 & relatedness < 3.5 ~ "Medium Relatedness",
      relatedness >= 3.5 & relatedness <= 5 ~ "High Relatedness",
      TRUE ~ NA_character_
    ),
    competence = case_when(
      competence >= 1 & competence < 2.5 ~ "Low Competence",
      competence >= 2.5 & competence < 3.5 ~ "Medium Competence",
      competence >= 3.5 & competence <= 5 ~ "High Competence",
      TRUE ~ NA_character_
    )
  )

contingency_table <- data_cleaned %>%
  group_by(autonomy, relatedness, competence) %>%
  summarise(count = n(), .groups = "drop") %>%
  complete(autonomy, relatedness, competence, fill = list(count = 0))

write_csv(recoded_data_df, "/Users/randkhunaizi/Downloads/STAT GP4 DATA/recode_final_final_recoded.csv")
write_csv(contingency_table_df, "/Users/randkhunaizi/Downloads/STAT GP4 DATA/contingency_table_recode_final_final.csv")


# Load useful packages ----
packages <- c("tidyverse", "hasseDiagram", "knitr", "kableExtra",
              "car", "psych", "parameters", "emmeans", "DescTools")
lapply(
  X = packages,
  FUN = library,
  character.only = TRUE,
  quietly = TRUE
)

# Set options ----
options(contrasts = c("contr.sum", "contr.poly"))
options(knitr.kable.NA = "")

# Load additional tools ----
source("https://raw.github.com/neilhatfield/STAT461/master/rScripts/ANOVATools.R")


#setwd("/Downloads/STAT_461_FINAL_PROJECT")

#file_path <- "Data/updated data as of 18:12:2024/recode_final_final_recoded (use for analysis).csv"

participantData <- read.csv("~/Downloads/recode_final.csv")
# View Structure and Summary ----
str(participantData)

# set as factor
participantData$competence <- as.factor(participantData$competence)
participantData$relatedness <- as.factor(participantData$relatedness)
```

````
participantData$autonomy <- as.factor(participantData$autonomy)
```
```{r}
## Descriptive Stats
psychStats <- psych::describeBy(
  positive_affect ~ autonomy + relatedness + competence,
  data = participantData,
  na.rm = TRUE,
  skew = TRUE,
  ranges = TRUE,
  quant = c(0.25, 0.75),
  IQR = TRUE,
  mat = TRUE,
  digits = 4
)


# Fit the ANOVA model
participantModel <- aov(
  positive_affect ~ competence * relatedness * autonomy,
  data = participantData
)

# Assessing Assumptions

```{r}
# QQ Plot for Residuals ----
car::qqPlot(
  x = residuals(participantModel),
  distribution = "norm",
  envelope = 0.90,
  id = FALSE,
  pch = 20,
  ylab = "Residuals"

)

psych::skew(participantModel$residuals)
psych::kurtosi(participantModel$residuals)


#density plot for residuals to help complement gaussian assumption


plot(density(residuals(participantModel)), col = "blue", lwd = 2,
     main = "Density Plot of Residuals", xlab = "Residuals")


# Tukey-Anscombe Plot for homoscedasticity
ggplot(
  data = data.frame(
    residuals = residuals(participantModel),
    fitted = fitted.values(participantModel)
  ),
  mapping = aes(x = fitted, y = residuals)
) +
  geom_point(size = 2) +
  geom_hline(
    yintercept = 0,
    linetype = "dashed",
    color = "grey50"
  ) +
  geom_smooth(
    formula = y ~ x,
    method = stats::loess,
    method.args = list(degree = 1),
    se = FALSE,
    linewidth = 0.5
  ) +
  theme_bw() +
  labs(
````
````

```
    x = "Fitted Values",
    y = "Residuals"
  )


ggplot(data.frame(residuals = residuals(participantModel),
                  fitted = fitted(participantModel)),
       aes(x = fitted, y = residuals)) +
    geom_point() +
    geom_hline(yintercept = 0, linetype = "dashed", color = "grey") +
    geom_smooth(method = "loess", se = FALSE) +
    theme_bw() +
    labs(x = "Fitted Values", y = "Residuals")
  theme_minimal()
```


```{r}
# Boxplot for all 3 Factors
box_data <- participantData %>%
  na.omit() %>%
  pivot_longer(cols = c(autonomy, relatedness, competence), names_to = "Predictor", values_to = "
      Value")

ggplot(box_data, aes(x = Value, y = positive_affect, fill = Predictor)) +
  geom_boxplot() +
  labs(x = "Predictors", y = "Positive Affect", title = "Boxplot of Predictors") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

ANOVA Test
parameters::model_parameters(
  model = participantModel,
  es_type = c("eta", "omega", "epsilon"),
  type = 3,
  drop = "(Intercept)",
  verbose = FALSE
) %>%
  dplyr::mutate(
    p = ifelse(
      test = is.na(p),
      yes = NA,
      no = pvalRound(p)
)
) %>%
  knitr::kable(
    digits = 3,
    row.names = FALSE,
    col.names = c("Source", "SS", "df", "MS", "F", "p-value",
                  "Partial Eta Sq.", "Partial Omega Sq.", "Partial Epsilon Sq."),
    format.args = list(big.mark = ","),
    align = c('l',rep('c',8)),
    booktab = TRUE
) %>%
  kableExtra::kable_styling(
    bootstrap_options = c("striped", "condensed"),
    font_size = 12,
    latex_options = c("scale_down", "HOLD_position")
)

```




# point estimates
pointEst <- dummy.coef(participantModel)  # Extract dummy coefficients
pointEst <- unlist(pointEst)  # Flatten into a vector

main_effects <- c(
  "Grand Mean",  # Overall average across all participants
```

```r
  levels(participantData$competence),
  levels(participantData$relatedness),
  levels(participantData$autonomy)
)

interaction_terms_2way <- expand.grid(
  competence = levels(participantData$competence),
  relatedness = levels(participantData$relatedness),
  autonomy = NA
)
interaction_terms_2way_aut <- expand.grid(
  competence = levels(participantData$competence),
  relatedness = NA,
  autonomy = levels(participantData$autonomy)
)
interaction_terms_2way_rel <- expand.grid(
  competence = NA,
  relatedness = levels(participantData$relatedness),
  autonomy = levels(participantData$autonomy)
)

interaction_terms_3way <- expand.grid(
  competence = levels(participantData$competence),
  relatedness = levels(participantData$relatedness),
  autonomy = levels(participantData$autonomy)
)

two_way_labels <- c(
  apply(interaction_terms_2way, 1, function(row) paste(na.omit(row), collapse = " x ")),
  apply(interaction_terms_2way_aut, 1, function(row) paste(na.omit(row), collapse = " x ")),
  apply(interaction_terms_2way_rel, 1, function(row) paste(na.omit(row), collapse = " x "))
)
three_way_labels <- apply(interaction_terms_3way, 1, paste, collapse = " x ")

row_names <- c(main_effects, two_way_labels, three_way_labels)

if (length(pointEst) > length(row_names)) {
  extra_terms <- names(pointEst)[(length(row_names) + 1):length(pointEst)]
  row_names <- c(row_names, extra_terms)
}

names(pointEst) <- row_names

# a tidy data frame for display
result <- data.frame(
  "Row Name" = names(pointEst),
  "Estimate" = pointEst
)

# table
result %>%
  knitr::kable(
    digits = 2,
    booktabs = TRUE,
    align = c("l", "c")
  ) %>%
  kableExtra::kable_styling(
    font_size = 12,
    latex_options = c("HOLD_position")
  )
```

```
#Competence Pairwise Comparisons
competencePostHoc <- emmeans::emmeans(
  object = participantModel,
  specs = pairwise ~ competence,
  adjust = "fdr",
  level = 0.88
)

knitr::kable(
  x = as.data.frame(competencePostHoc$contrasts),
  digits = 4,
  col.names = c("Pairwise Comparison", "Difference", "SE", "DF", "t", "p-value"),
  align = "lccccc",
  booktabs = TRUE
) %>%
  kableExtra::kable_styling(
    font_size = 12,
    latex_options = c("HOLD_position")
  )

#Autonomy Pairwise Comparisons
autonomyPostHoc <- emmeans::emmeans(
  object = participantModel,
  specs = pairwise ~ autonomy,
  adjust = "fdr",
  level = 0.88
)

knitr::kable(
  x = as.data.frame(autonomyPostHoc$contrasts),
  digits = 4,
  col.names = c("Pairwise Comparison", "Difference", "SE", "DF", "t", "p-value"),
  align = "lccccc",
  booktabs = TRUE
) %>%
  kableExtra::kable_styling(
    font_size = 12,
    latex_options = c("HOLD_position")
  )

# Relatedness Pairwise Comparisons
relatednessPostHoc <- emmeans::emmeans(
  object = participantModel,
  specs = pairwise ~ relatedness,
  adjust = "fdr",
  level = 0.88
)

knitr::kable(
  x = as.data.frame(relatednessPostHoc$contrasts),
  digits = 4,
  col.names = c("Pairwise Comparison", "Difference", "SE", "DF", "t", "p-value"),
  align = "lccccc",
  booktabs = TRUE
) %>%
  kableExtra::kable_styling(
    font_size = 12,
    latex_options = c("HOLD_position")
  )



# Create the boxplot
ggplot(participantData, aes(x = autonomy, y = positive_affect, fill = autonomy)) +
  geom_boxplot(alpha = 0.7, color = "black") +  # Add boxplot
```

```
  labs(
    title = "Boxplot of Positive Affect by Autonomy",
    x = "Autonomy",
    y = "Positive Affect"
  ) +
  theme_minimal() +
  theme(
    legend.position = "none",  # Remove legend if unnecessary
    axis.text.x = element_text(angle = 45, hjust = 1)  # Adjust x-axis labels for readability
  )


participantData <- participantData %>%
  mutate(
    competence = factor(competence, levels = c("Low Competence", "Medium Competence", "High Competence"))
  )

# create boxplot
ggplot(participantData, aes(x = competence, y = positive_affect, fill = competence)) +
  geom_boxplot(alpha = 0.7, color = "black") +  # Add boxplot
  labs(
    title = "Boxplot of Positive Affect by Competence",
    x = "Competence",
    y = "Positive Affect"
  ) +
  theme_minimal() +
  theme(
    legend.position = "none"    axis.text.x = element_text(angle = 45, hjust = 1)    )


participantData <- participantData %>%
  mutate(
    relatedness = factor(relatedness, levels = c("Low Relatedness", "Medium Relatedness", "High Relatedness"))
  )

# boxplot
ggplot(participantData, aes(x = relatedness, y = positive_affect, fill = relatedness)) +
  geom_boxplot(alpha = 0.7, color = "black") +  # Add boxplot
  labs(
    title = "Boxplot of Positive Affect by Relatedness",
    x = "Relatedness",
    y = "Positive Affect"
  ) +
  theme_minimal() +
  theme(
    legend.position = "none",      axis.text.x = element_text(angle = 45, hjust = 1)  # Adjust x-axis labels for readability
  )



# density plot- autonomy
ggplot(participantData, aes(x = positive_affect, fill = autonomy)) +
  geom_density(alpha = 0.7) +
  labs(
    title = "Density Plot of Positive Affect by Autonomy",
    x = "Positive Affect",
    y = "Density"
  ) +
  theme_minimal() +
  theme(
    legend.title = element_blank(),
    legend.position = "top"
  )



# density plot - competence
ggplot(participantData, aes(x = positive_affect, fill = competence)) +
```

```
  geom_density(alpha = 0.7) +
  labs(
    title = "Density Plot of Positive Affect by Competence",
    x = "Positive Affect",
    y = "Density"
  ) +
  theme_minimal() +
  theme(
    legend.title = element_blank(),
    legend.position = "top"
  )

# density plot- relatedness
ggplot(participantData, aes(x = positive_affect, fill = relatedness)) +
  geom_density(alpha = 0.7) +
  labs(
    title = "Density Plot of Positive Affect by Relatedness",
    x = "Positive Affect",
    y = "Density"
  ) +
  theme_minimal() +
  theme(
    legend.title = element_blank(),
    legend.position = "top"
  )


#histogram- competence
ggplot(participantData, aes(x = positive_affect, fill = competence)) +
  geom_histogram(binwidth = 0.5, position = "dodge", alpha = 0.7, color = "black") +
  labs(
    title = "Histogram of Positive Affect by Competence",
    x = "Positive Affect",
    y = "Count"
  ) +
  theme_minimal() +
  theme(
    legend.title = element_blank(),
    legend.position = "top"
  )

# histogram- autonomy
ggplot(participantData, aes(x = positive_affect, fill = autonomy)) +
  geom_histogram(binwidth = 0.5, position = "dodge", alpha = 0.7, color = "black") +
  labs(
    title = "Histogram of Positive Affect by Autonomy",
    x = "Positive Affect",
    y = "Count"
  ) +
  theme_minimal() +
  theme(
    legend.title = element_blank(),
    legend.position = "top"
  )

# histogram- relatedness
ggplot(participantData, aes(x = positive_affect, fill = relatedness)) +
  geom_histogram(binwidth = 0.5, position = "dodge", alpha = 0.7, color = "black") +
  labs(
    title = "Histogram of Positive Affect by Relatedness",
    x = "Positive Affect",
    y = "Count"
  ) +
  theme_minimal() +
  theme(
    legend.title = element_blank(),
    legend.position = "top"
  )
```

```
#violin plot


# Create the violin plot
ggplot(participantData, aes(x = autonomy, y = positive_affect, fill = autonomy)) +
  geom_violin(trim = FALSE, alpha = 0.7, color = "black") +
  labs(
    title = "Violin Plot of Positive Affect by Autonomy",
    x = "Autonomy",
    y = "Positive Affect"
  ) +
  theme_minimal() +
  theme(
    legend.position = "none",
    axis.text.x = element_text(angle = 45, hjust = 1)
  )

# Create the violin plot
ggplot(participantData, aes(x = competence, y = positive_affect, fill = competence)) +
  geom_violin(trim = FALSE, alpha = 0.7, color = "black") +    labs(
    title = "Violin Plot of Positive Affect by Competence",
    x = "Competence",
    y = "Positive Affect"
  ) +
  theme_minimal() +
  theme(
    legend.position = "none",      axis.text.x = element_text(angle = 45, hjust = 1)   )


# Create the violin plot
ggplot(participantData, aes(x = relatedness, y = positive_affect, fill = relatedness)) +
  geom_violin(trim = FALSE, alpha = 0.7, color = "black") +    labs(
    title = "Violin Plot of Positive Affect by Relatedness",
    x = "Relatedness",
    y = "Positive Affect"
  ) +
  theme_minimal() +
  theme(
    legend.position = "none",
    axis.text.x = element_text(angle = 45, hjust = 1)

# compute Marginal Means for Autonomy
autonomyMeans <- emmeans(
  object = participantModel,
  specs = ~ autonomy,
  level = 0.88,
  adjust = "fdr"      )

# Convert to Data Frame
autonomyMeans <- as.data.frame(autonomyMeans)

# Display Table for Autonomy
autonomyMeans %>%
  knitr::kable(
    digits = 3,
    col.names = c("Autonomy Level", "Marginal Mean", "SE", "df",
                  "Lower Bound", "Upper Bound"),
    booktabs = TRUE
  ) %>%
  kableExtra::kable_styling(
    font_size = 12,
    latex_options = c("HOLD_position")
  )


# competence Marginal Means
competenceMeans <- emmeans(
  object = participantModel,
  specs = ~ competence,
  level = 0.88,
  adjust = "fdr"
```

```
)

competenceMeans <- as.data.frame(competenceMeans)

competenceMeans %>%
  knitr::kable(
    digits = 3,
    col.names = c("Competence Level", "Marginal Mean", "SE", "df",
                  "Lower Bound", "Upper Bound"),
    booktabs = TRUE
  ) %>%
  kableExtra::kable_styling(
    font_size = 12,
    latex_options = c("HOLD_position")
  )

# Relatedness Marginal Means
relatednessMeans <- emmeans(
  object = participantModel,
  specs = ~ relatedness,
  level = 0.88,
  adjust = "fdr"
)

relatednessMeans <- as.data.frame(relatednessMeans)

relatednessMeans %>%
  knitr::kable(
    digits = 3,
    col.names = c("Relatedness Level", "Marginal Mean", "SE", "df",
                  "Lower Bound", "Upper Bound"),
    booktabs = TRUE
  ) %>%
  kableExtra::kable_styling(
    font_size = 12,
    latex_options = c("HOLD_position")
  )


# Get the appropriate means for Competence
competenceMeans <- emmeans::emmeans(
  object = participantModel,
  specs = ~ competence
)

# contrasts
competenceContrasts <- emmeans::contrast(
  object = competenceMeans,
  method = list(
    "High & Medium Competence vs. Low Competence" = c(-1, 0.5, 0.5) # Adjust coefficients as
        needed
  ),
  adjust = "fdr"
)


# effect sizes and table
competenceContrastTable <- as.data.frame(competenceContrasts) %>%
  dplyr::mutate(
    cohen = effectsize::t_to_d(t = t.ratio, df_error = df)$d,
    ps = pnorm(cohen) # Calculate Prob. of Superiority
  ) %>%
  kable(
    digits = 4,
    col.names = c("Contrast", "Difference", "SE", "DF", "t Statistic",
                  "p-value", "Cohen's d", "Prob. of Superiority"),
    align = "lccccccc",
    booktabs = TRUE
  ) %>%
  kableExtra::kable_styling(
    bootstrap_options = c("striped", "condensed"),
```

```
    font_size = 12,
    latex_options = c("HOLD_position", "scale_down")
  )

competenceContrastTable


# Get the appropriate means for Autonomy
autonomyMeans <- emmeans::emmeans(
  object = participantModel,
  specs = ~ autonomy
)

# contrasts
autonomyContrasts <- emmeans::contrast(
  object = autonomyMeans,
  method = list(
    "High & Medium Autonomy vs. Low Autonomy" = c(-1, 0.5, 0.5)
  ),
  adjust = "fdr"
)

# effect sizes and table
autonomyContrastTable <- as.data.frame(autonomyContrasts) %>%
  dplyr::mutate(
    cohen = effectsize::t_to_d(t = t.ratio, df_error = df)$d,
    ps = pnorm(cohen)
  ) %>%
  kable(
    digits = 4,
    col.names = c("Contrast", "Difference", "SE", "DF", "t Statistic",
                  "p-value", "Cohen's d", "Prob. of Superiority"),
    align = "lccccccc",
    booktabs = TRUE
  ) %>%
  kableExtra::kable_styling(
    bootstrap_options = c("striped", "condensed"),
    font_size = 12,
    latex_options = c("HOLD_position", "scale_down")
  )

autonomyContrastTable


# Get the appropriate means for Relatedness
relatednessMeans <- emmeans::emmeans(
  object = participantModel,
  specs = ~ relatedness
)

# contrasts
relatednessContrasts <- emmeans::contrast(
  object = relatednessMeans,
  method = list(
    "High & Medium Relatedness vs. Low Relatedness" = c(-1, 0.5, 0.5)
  ),
  adjust = "fdr"
)

# effect sizes and nice table
relatednessContrastTable <- as.data.frame(relatednessContrasts) %>%
  dplyr::mutate(
    cohen = effectsize::t_to_d(t = t.ratio, df_error = df)$d,
    ps = pnorm(cohen)
  ) %>%
  kable(
    digits = 4,
    col.names = c("Contrast", "Difference", "SE", "DF", "t Statistic",
                  "p-value", "Cohen's d", "Prob. of Superiority"),
    align = "lccccccc",
    booktabs = TRUE
```

```r
  ) %>%
  kableExtra::kable_styling(
    bootstrap_options = c("striped", "condensed"),
    font_size = 12,
    latex_options = c("HOLD_position", "scale_down")
  )

relatednessContrastTable


# Get the appropriate means for Competence
competenceMeans <- emmeans::emmeans(
  object = participantModel,
  specs = ~ competence
)

# contrasts
competenceContrasts <- emmeans::contrast(
  object = competenceMeans,
  method = list(
    "High & Medium Competence vs. Low Competence" = c(-1, 0.5, 0.5) # Adjust coefficients as needed
  ),
  adjust = "fdr"
)


# effect size and table
competenceContrastTable <- as.data.frame(competenceContrasts) %>%
  dplyr::mutate(
    cohen = effectsize::t_to_d(t = t.ratio, df_error = df)$d,
    ps = pnorm(cohen)   ) %>%
  kable(
    digits = 4,
    col.names = c("Contrast", "Difference", "SE", "DF", "t Statistic",
                  "p-value", "Cohen's d", "Prob. of Superiority"),
    align = "lccccccc",
    booktabs = TRUE
  ) %>%
  kableExtra::kable_styling(
    bootstrap_options = c("striped", "condensed"),
    font_size = 12,
    latex_options = c("HOLD_position", "scale_down")
  )

competenceContrastTable


# Get the appropriate means for Autonomy
autonomyMeans <- emmeans::emmeans(
  object = participantModel,
  specs = ~ autonomy
)

# Apply the contrasts
autonomyContrasts <- emmeans::contrast(
  object = autonomyMeans,
  method = list(
    "High & Medium Autonomy vs. Low Autonomy" = c(-1, 0.5, 0.5)
  ),
  adjust = "fdr"
)

# Add effect sizes and make a nice-looking table
autonomyContrastTable <- as.data.frame(autonomyContrasts) %>%
  dplyr::mutate(
    cohen = effectsize::t_to_d(t = t.ratio, df_error = df)$d,
    ps = pnorm(cohen)
  ) %>%
  kable(
    digits = 4,
```

```r
    col.names = c("Contrast", "Difference", "SE", "DF", "t Statistic",
                  "p-value", "Cohen's d", "Prob. of Superiority"),
    align = "lcccccccc",
    booktabs = TRUE
  ) %>%
  kableExtra::kable_styling(
    bootstrap_options = c("striped", "condensed"),
    font_size = 12,
    latex_options = c("HOLD_position", "scale_down")
  )

autonomyContrastTable


#  means for Relatedness
relatednessMeans <- emmeans::emmeans(
  object = participantModel,
  specs = ~ relatedness
)

# contrasts
relatednessContrasts <- emmeans::contrast(
  object = relatednessMeans,
  method = list(
    "High & Medium Relatedness vs. Low Relatedness" = c(-1, 0.5, 0.5)
  ),
  adjust = "fdr"
)

# effect sizes & table
relatednessContrastTable <- as.data.frame(relatednessContrasts) %>%
  dplyr::mutate(
    cohen = effectsize::t_to_d(t = t.ratio, df_error = df)$d,
    ps = pnorm(cohen)
  ) %>%
  kable(
    digits = 4,
    col.names = c("Contrast", "Difference", "SE", "DF", "t Statistic",
                  "p-value", "Cohen's d", "Prob. of Superiority"),
    align = "lcccccccc",
    booktabs = TRUE
  ) %>%
  kableExtra::kable_styling(
    bootstrap_options = c("striped", "condensed"),
    font_size = 12,
    latex_options = c("HOLD_position", "scale_down")
  )

relatednessContrastTable










## Competence Pairwise Comparisons
competencePostHoc <- emmeans::emmeans(
  object = participantModel,
  specs = pairwise ~ competence,
  adjust = "fdr",
  level = 0.88
)

knitr::kable(
  x = as.data.frame(competencePostHoc$contrasts),
  digits = 4,
  col.names = c("Pairwise Comparison", "Difference", "SE", "DF", "t", "p-value"),
```

```r
  align = "lccccc",
  booktabs = TRUE
) %>%
  kableExtra::kable_styling(
    font_size = 12,
    latex_options = c("HOLD_position")
  )

## Autonomy Pairwise Comparisons
autonomyPostHoc <- emmeans::emmeans(
  object = participantModel,
  specs = pairwise ~ autonomy,
  adjust = "fdr",
  level = 0.88
)

knitr::kable(
  x = as.data.frame(autonomyPostHoc$contrasts),
  digits = 4,
  col.names = c("Pairwise Comparison", "Difference", "SE", "DF", "t", "p-value"),
  align = "lccccc",
  booktabs = TRUE
) %>%
  kableExtra::kable_styling(
    font_size = 12,
    latex_options = c("HOLD_position")
  )

## Relatedness Pairwise Comparisons
relatednessPostHoc <- emmeans::emmeans(
  object = participantModel,
  specs = pairwise ~ relatedness,
  adjust = "fdr",
  level = 0.88
)

knitr::kable(
  x = as.data.frame(relatednessPostHoc$contrasts),
  digits = 4,
  col.names = c("Pairwise Comparison", "Difference", "SE", "DF", "t", "p-value"),
  align = "lccccc",
  booktabs = TRUE
) %>%
  kableExtra::kable_styling(
    font_size = 12,
    latex_options = c("HOLD_position")
  )




#point estimates
pointEst <- dummy.coef(participantModel)
pointEst <- unlist(pointEst)

# Generate row names for the model terms
main_effects <- c(
  "Grand Mean",
  levels(participantData$competence),
  levels(participantData$relatedness),
  levels(participantData$autonomy)
)

# Generate labels for two-way and three-way interaction terms
interaction_terms_2way <- expand.grid(
  competence = levels(participantData$competence),
  relatedness = levels(participantData$relatedness),
  autonomy = NA
)
interaction_terms_2way_aut <- expand.grid(
  competence = levels(participantData$competence),
```

````
  relatedness = NA,
  autonomy = levels(participantData$autonomy)
)
interaction_terms_2way_rel <- expand.grid(
  competence = NA,
  relatedness = levels(participantData$relatedness),
  autonomy = levels(participantData$autonomy)
)
interaction_terms_3way <- expand.grid(
  competence = levels(participantData$competence),
  relatedness = levels(participantData$relatedness),
  autonomy = levels(participantData$autonomy)
)

# Combine labels
two_way_labels <- c(
  apply(interaction_terms_2way, 1, function(row) paste(na.omit(row), collapse = " x ")),
  apply(interaction_terms_2way_aut, 1, function(row) paste(na.omit(row), collapse = " x ")),
  apply(interaction_terms_2way_rel, 1, function(row) paste(na.omit(row), collapse = " x "))
)
three_way_labels <- apply(interaction_terms_3way, 1, paste, collapse = " x ")

# row names to pt. estimates
names(pointEst) <- row_names

# data frame
result <- data.frame("Row Name" = names(pointEst), "Estimate" = pointEst)

# Display table
result %>%
  knitr::kable(
    digits = 2,
    # caption = "Point Estimates from the Participant Data Study",
    booktabs = TRUE,
    align = c("l", "c")
  ) %>%
  kableExtra::kable_styling(
    font_size = 12,
    latex_options = c("HOLD_position")
  )




```







`







```
````