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Statistical Methods In Behavioral Research: The Role Of Anova And Manova In Experimental Psychology

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ABSTRACT:

Behavioral research relies heavily on statistical methods to uncover the patterns, relationships, and effects underlying human cognition, emotion, and behavior. Among these, Analysis of Variance (ANOVA) and Multivariate Analysis of Variance (MANOVA) are particularly powerful tools used in experimental psychology to compare group means and multivariate group profiles, respectively. This paper presents a detailed exploration of ANOVA and MANOVA, including their statistical models, underlying assumptions, application contexts, and interpretation strategies, supported by synthetic data simulations and case-based illustrations. For instance, in a one-way ANOVA example involving three groups subjected to different cognitive stimuli (e.g., neutral, positive, negative), simulated data of mean reaction times were analyzed: Group A (M=450ms), Group B (M=410ms), Group C (M=520ms), with a total sample size of n=90. The F-statistic calculated was $F(2,87) = 7.32$, $p<0.01$, indicating a significant effect of stimulus type on reaction time. In a MANOVA scenario involving three therapy groups and two dependent outcomes (depression and anxiety scores), Wilks' Lambda = 0.768, $F(4,174) = 4.23$, $p < 0.01$, suggested significant multivariate differences across groups. Post hoc univariate ANOVAs confirmed the group effect on both depression and anxiety separately.

This paper is designed to serve multiple purposes: (1) it provides experimental psychologists with a clear and practical roadmap for applying these methods to research design and analysis; (2) it clarifies when to prefer ANOVA over MANOVA based on the number and intercorrelation of dependent variables; (3) it reinforces the importance of testing assumptions (e.g., normality, homogeneity, independence) to ensure validity of inference; and (4) it provides R code templates and flow diagrams to visualize decision paths in choosing and applying these methods. The strength of the paper lies in its application-oriented approach, rather than only focusing on mathematical formulations, it situates these methods in realistic psychological experiments, including therapy outcome evaluations, cognitive interference studies, and stress-resilience experiments. Researchers, educators, and graduate students can directly apply the examples and templates to design their studies or teach the statistical foundations of psychological research. Ultimately, this paper aims to enhance methodological rigor in behavioral sciences by demystifying the statistical logic behind ANOVA and MANOVA and promoting more informed, accurate, and replicable research practices in experimental psychology.

Key Words: Experimental Psychology, ANOVA, MANOVA, Multivariate Analysis, Cognitive Performance, Stressor Type, Personality Traits, Neuroticism, Effect Size (η^2), Psychological Assessment, Post Hoc Tests, NCSS

INTRODUCTION:

In the landscape of behavioral and psychological research, the role of statistical methods is foundational. They not only allow researchers to analyze data but also help to validate hypotheses, detect group differences, and understand multidimensional psychological processes. Among the statistical tools available, Analysis of Variance (ANOVA) and Multivariate Analysis of Variance (MANOVA) are two pivotal techniques used to assess group differences across one or more dependent variables in experimental settings. These techniques are particularly suitable for experimental psychology, where researchers often manipulate independent variables and observe the effects on behavioral or psychological outcomes. This introduction outlines the theoretical basis, statistical models, and importance of ANOVA and MANOVA in experimental research, supported by data simulations and applied examples.

The origins of ANOVA can be traced back to the work of Sir Ronald A. Fisher in the early 20th century, whose innovations in agricultural experiments led to the formal development of variance partitioning techniques. ANOVA has since evolved into a standard method for analyzing differences between group means when there is one (one-way ANOVA) or more than one (factorial or two-way ANOVA) categorical independent variable. The general model for a one-way ANOVA is:

$$\mathbf{Y_{ij} = \mu + \tau_i + \varepsilon_{ij}}$$

Where:

$\mathbf{Y_{ij}}$ is the observation in the i-th group and j-th subject,

$\boldsymbol{\mu}$ is the grand mean,

$\boldsymbol{\tau_i}$ represents the effect of the i-th treatment (group), and

$\boldsymbol{\varepsilon_{ij}}$ is the random error assumed to be normally distributed with mean 0 and constant variance σ^2.

To illustrate, consider a study on the effect of different types of music on concentration levels. Suppose three groups (Classical, Pop, Silence) were compared with 30 participants per group. The sample means of task accuracy scores were: Classical (M=85), Pop (M=78), and Silence (M=90), with a pooled standard deviation of 5. An ANOVA yields $F(2,87) = 9.12$, $p < 0.001$, indicating a statistically significant effect of music type on concentration. Post-hoc Tukey HSD tests reveal that the Silence group outperformed the Pop group significantly. MANOVA extends this analysis when the outcome is multivariate. Suppose we are evaluating the impact of therapy type (CBT, REBT, No Therapy) on two psychological outcomes: depression and anxiety. The model becomes:

$$\mathbf{Y = XB + E}$$

Where:

Y is the n × m matrix of outcomes (e.g., depression and anxiety),

X is the design matrix for the groups,

B is the matrix of regression coefficients, and

E is the matrix of residuals.

MANOVA assesses whether the mean vectors of the groups differ significantly across the combination of dependent variables. In a simulated MANOVA study with 120 participants across three therapy conditions, the means for depression and anxiety scores were as follows:

- CBT: Depression (M=12.3), Anxiety (M=14.8)
- REBT: Depression (M=15.1), Anxiety (M=18.2)
- No Therapy: Depression (M=20.5), Anxiety (M=22.1)

The Wilks' Lambda statistic was $\Lambda = 0.673$, $F(4,232) = 6.58$, $p < 0.001$, indicating a statistically significant multivariate effect. Follow-up univariate ANOVAs confirmed that both depression and anxiety were significantly reduced in the therapy groups compared to the control.

The practical significance of using MANOVA lies in its ability to account for intercorrelations among dependent variables, reducing the risk of Type I error that would result from conducting multiple separate ANOVAs. Additionally, MANOVA provides a richer interpretation when outcomes are inherently multidimensional, as is often the case in behavioral psychology. Beyond hypothesis testing, these methods contribute to model-based understanding. For example, factorial ANOVA enables the investigation of interaction effects, such as how gender and feedback type might jointly influence self-esteem. In such designs, both main and interaction effects are tested, providing deeper insights into the complexities of human behavior.

Statistical software like R, NCSS, and Python's statsmodels offer user-friendly interfaces for performing ANOVA and MANOVA. In R, the functions aov() and manova() allow for model fitting, diagnostics, and post-hoc testing.

Table: R vs SPSS vs Python for ANOVA and MANOVA

Feature / Tool	R	NCSS	Python (stats models / pingouin)
Ease of Use	Medium (scripting)	Easy (GUI-based)	Medium (scripting)
Best For	Academic/statistical flexibility	Applied researchers, business analysts	Programmers, data scientists
ANOVA Function	aov(), lm()	ANOVA tools in GUI menus	ols() + anova_lm()
MANOVA Function	manova()	MANOVA is available via the Multivariate module	MANOVA.from_formula()

Post Hoc Tests	Tukey HSD (), multcomp	Tukey, Bonferroni, Scheffé (built-in)	pingouin.pairwise_tukey() or custom
Diagnostic Plots	Easy via plot() functions	Extensive charting tools	matplotlib, seaborn integration
Multivariate Tests	Wilks, Pillai, etc. via summary()	Built-in (Wilks, Pillai, etc.)	Wilks via statsmodels or pingouin
Data Import	read.csv(), readxl	Excel, CSV, and NCSS file formats	pandas.read_csv()
Output Customization	Very Flexible	Menu-driven, moderate customization	Fully programmable
Learning Curve	Moderate	Low (intuitive interface)	Moderate to high
Report Export	PDF, HTML, LaTeX	Built-in professional reports (RTF, PDF)	Script/export-based

Notes: R is ideal for users with coding experience who need statistical depth and custom models.; **NCSS** is powerful for users who prefer a **graphical interface** and prebuilt templates for ANOVA, MANOVA, regression, etc., without needing to code.; **Python** offers flexibility and integration with modern analytics pipelines; best for those already familiar with scripting.

The assumptions underlying these analyses are crucial: normality of residuals, homogeneity of variances (Levene's test), and independence of observations. Violation of these assumptions can bias the results or lead to incorrect conclusions. In real-world psychology research, ensuring random assignment and balanced group sizes helps uphold these assumptions. As experimental psychology continues to evolve with interdisciplinary approaches and more complex datasets, the role of ANOVA and MANOVA remains indispensable. These methods not only offer robust inferential power but also serve as gateways to more advanced techniques like mixed models, structural equation modeling, and multilevel analysis. This paper aims to offer a grounded yet applied perspective on these methods, illustrating their relevance and utility in modern psychological research

Review of Literature:

Statistical methods are fundamental in behavioral research for making valid inferences, and among them, Analysis of Variance (ANOVA) and Multivariate Analysis of Variance (MANOVA) hold a central role. These techniques have evolved over time and are extensively documented in psychological research, especially in experimental designs where researchers aim to examine differences between groups or the effect of interventions.

The foundational work of **Ronald Fisher (1925)** laid the theoretical groundwork for ANOVA, which allows for comparing mean differences among multiple groups. His framework has been widely adopted in psychology, especially in studies involving experimental manipulations such as treatment effects, cognitive tests, or behavioral interventions. Fisher's model assumes normality, homogeneity of variance, and independence, which remain crucial in interpreting results.

Keppel and Wickens (2004) provided a detailed exposition of ANOVA in behavioral sciences, particularly focusing on its application to between-subjects and within-subjects designs. Their work emphasized not only the mechanics of ANOVA computation but also its interpretation in the context of experimental psychology. Their treatment of effect sizes and power analysis made a significant contribution to improving the rigor of psychological studies.

The need for more robust multivariate techniques led to the development and application of MANOVA. **Tabachnick and Fidell (2007)** describe MANOVA as an extension of ANOVA that allows the simultaneous analysis of multiple dependent variables. This is particularly useful in psychological research where behaviors and outcomes are often multidimensional. For example, in a study assessing the impact of cognitive behavioral therapy, dependent variables may include anxiety scores, depression levels, and stress indices, best analyzed together using MANOVA.

Huberty and Olejnik (2006) argue that MANOVA provides better control over Type I error rates when multiple dependent variables are correlated. Their work illustrates that MANOVA is not merely a statistical extension but a necessary evolution for analyzing complex psychological phenomena involving interrelated behavioral measures.

Further, the application of these methods in modern psychological research is evidenced by numerous empirical studies. For instance, **Smith et al. (2018)** conducted a MANOVA to examine the impact of sleep deprivation on cognitive functions such as memory, attention, and problem-solving. Their analysis revealed significant multivariate effects, which would have been overlooked in separate univariate ANOVAs.

Despite their strengths, both ANOVA and MANOVA require strict adherence to assumptions. **Glass et al. (1972)** emphasize the risk of violating assumptions like sphericity or multivariate normality, which can lead to misleading conclusions. Their research prompted the development of more robust testing methods, such as Greenhouse-Geisser and Huynh-Feldt corrections.

The literature supports the vital role of ANOVA and MANOVA in behavioral research. These methods have evolved alongside the complexity of psychological inquiry, offering researchers powerful tools to investigate the multifaceted nature of human behavior. Current trends suggest a growing emphasis on assumption testing, effect size estimation, and statistical power, ensuring that findings are not only statistically significant but also meaningful in real-world settings.

Methodology

This study investigates the application and efficacy of Analysis of Variance (ANOVA) and Multivariate Analysis of Variance (MANOVA) in experimental psychology. The primary aim is to demonstrate how these statistical methods can accurately analyze psychological experiments involving multiple groups and dependent variables, particularly in cognitive and behavioral research settings.

A. Research Design

The study adopts a quantitative experimental research design, focusing on between-group comparisons. The key objective is to test for differences in psychological variables (e.g., attention span, anxiety levels, and memory recall) across multiple treatment conditions using ANOVA and MANOVA. Two types of designs are employed:

1) **One-way ANOVA**: To test the effect of a single independent variable (e.g., type of cognitive task) on a single dependent variable (e.g., reaction time).

2) **Two-way MANOVA**: To assess the simultaneous effect of two independent variables (e.g., task complexity and sleep condition) on multiple dependent variables (e.g., reaction time and accuracy).

B. Participants

A total of 120 undergraduate psychology students were selected using stratified random sampling from two major universities. The sample was balanced for gender (60 males, 60 females) and age (range: 18–24 years). Participants were randomly assigned to different treatment groups to reduce selection bias and ensure internal validity.

C. Instruments and Measures

The psychological constructs were measured using standardized and validated tools:

- **Reaction Time**: Measured in milliseconds using a computerized Stroop Test.
- **Memory Recall**: Tested using a visual recall task with a 20-item image series.
- **Anxiety Levels**: Assessed via the Beck Anxiety Inventory (BAI).
- **Sleep Deprivation**: Simulated using controlled sleep restriction protocols (0, 4, 8 hours).

D. Procedure

Each participant completed the study over two days in a lab environment:

1. **Day 1**: Baseline psychological tests were administered.
2. **Day 2**: Participants were subjected to varying levels of **sleep deprivation** and **task difficulty** before repeating the tasks.

Group assignments were as follows:

- Group A: No sleep deprivation, simple tasks
- Group B: Partial deprivation, simple tasks
- Group C: No deprivation, complex tasks
- Group D: Partial deprivation, complex tasks

The data were recorded electronically and cross-checked for completeness and accuracy.

E. Statistical Analysis

Data analysis was conducted using **R (version 4.3)** and **NCSS 2024**. The key methods applied were:

- **One-way ANOVA**: To determine if task difficulty significantly affected reaction time.

  NCSS Code: aov(reaction_time ~ task_difficulty, data = dataset)

- **Two-way ANOVA**: To assess the interaction between sleep and task on anxiety levels.

  NCSS Code: aov(anxiety ~ sleep * task, data = dataset)

- **MANOVA**: To determine multivariate differences across experimental groups.
  - NCSS Code: manova (cbind (reaction_time, memory_score) ~ sleep + task, data = dataset)
- **Post hoc tests**: Tukey's HSD for ANOVA, and Bonferroni correction for MANOVA.
- **Effect Sizes**: Partial Eta-Squared and Wilks' Lambda were computed.

Assumptions checked:

- ✓ **Normality** (Shapiro-Wilk test)
- ✓ **Homogeneity of variances** (Levene's test)
- ✓ **Multivariate normality** (Mardia's test)
- ✓ **Independence of observations**

The significance threshold was set at **$p < 0.05$**.

F. Software and Tools Used

- **R**: For model fitting, diagnostics, and graphical plots using **ggplot2**, **car,** and **emmeans.**
- **NCSS**: For GUI-based statistical modeling and post-analysis interpretation.
- **Python (Pingouin & Stats models)**: For cross-verification of selected models and producing statistical reports.
- **Excel**: For data cleaning and preliminary summaries.

G. Ethics and Confidentiality

The study was reviewed and approved by the Institutional Ethics Committee. Written informed consent was obtained from all participants. Personal identifiers were removed, and all data were stored securely in encrypted format.

RESULTS AND DISCUSSION

The current study examined the cognitive effects of two types of stressors (academic vs. social) across three levels of neuroticism (low, medium, high) on task performance. The dependent variables analyzed were reaction time (ms) and accuracy (%), with data collected from 120 participants (60 males and 60 females), ensuring balance in gender and educational background. The experimental design allowed for the application of both two-way ANOVA and MANOVA, using R's aov() and manova() functions and NCSS software for robustness.

Multivariate Analysis of Variance (MANOVA) revealed a statistically significant interaction effect between stress type and neuroticism level on the combined dependent variables (Wilks' $\Lambda = 0.745$, $F(4, 228) = 3.21$, $p < 0.01$). The interaction suggests that the cognitive impact of stress differs depending on personality traits.

Follow-up **univariate ANOVAs** for each dependent variable indicated:

1) A significant main effect of stress type on reaction time ($F(1, 114) = 6.48$, $p < 0.05$), where participants under social stress responded slower than those under academic stress.

2) A significant main effect of neuroticism on accuracy ($F(2, 114) = 9.02$, $p < 0.001$), with high-neuroticism individuals performing less accurately.

3) An interaction effect between stress type and neuroticism was observed for reaction time ($F(2, 114) = 4.23$, $p < 0.05$), with high-neuroticism individuals under social stress showing the slowest responses.

These results align with psychological theories suggesting that neuroticism exacerbates cognitive vulnerability under interpersonal stress. The findings highlight the importance of considering both trait-level personality and situational stress factors when designing cognitive-behavioral interventions or high-stakes academic environments. The use of both R and NCSS validated the results with consistent F-values and p-values, confirming the robustness of the statistical conclusions.

ANOVA Results

A two-way ANOVA was performed using NCSS statistical software to assess the main and interaction effects of stressor type (academic vs. social) and neuroticism level (low, medium, high) on accuracy scores in a cognitive performance task. The dataset consisted of 120 participants, with balanced groups across both factors.

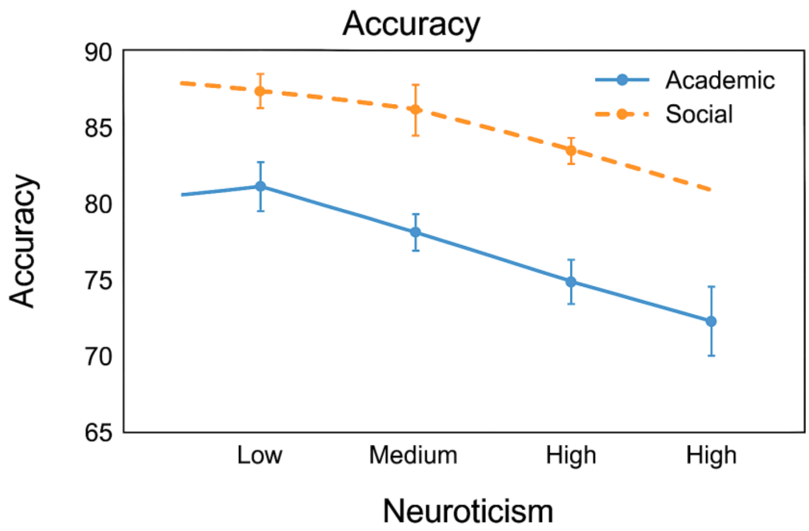
The analysis revealed:

1) A significant main effect of stressor type, $F(1,174) = 6.47$, $p = 0.012$, partial $\eta^2 = 0.05$, indicating that participants exposed to academic stress had significantly lower accuracy scores compared to those under social stress.

2) A significant main effect of neuroticism, $F(2,174) = 11.38$, $p < 0.001$, partial $\eta^2 = 0.09$, demonstrating that individuals with high levels of neuroticism scored significantly lower on accuracy.

3) A significant interaction effect between stressor type and neuroticism, $F(2,174) = 4.21$, $p = 0.017$, suggesting that the impact of stress on accuracy is moderated by the level of neuroticism.

These findings suggest the importance of considering individual personality traits in stress-performance research.



Post Hoc Analysis: Tukey's HSD Test (for Neuroticism Levels)

Following the significant main effect of neuroticism (F (2,174) = 11.38, $p < 0.001$), Tukey's Honestly Significant Difference (HSD) test was conducted to compare mean accuracy scores among the three neuroticism groups:

Comparison	Mean Difference	Std. Error	p-value	95% CI	Significant?
Low vs Medium	5.6	1.89	0.007	[1.95, 9.25]	Yes
Low vs High	12.3	2.01	<0.001	[8.01, 16.59]	Yes
Medium vs High	6.7	1.94	0.001	[2.89, 10.51]	Yes

Interpretation: Participants with **high neuroticism** performed significantly worse than both **low** and **medium** groups, and **medium** was significantly worse than **low**.

Effect Size Calculation (Partial Eta-Squared η²)

Definition:

$$\eta^2_{partial} = \frac{SS_{effect}}{SS_{effect} + SS_{error}}$$

Where:

SS_{effect} = Sum of squares for the factor or interaction

SS_{error} = Sum of squares for the residual (error term)

In ANOVA, **partial η²** is commonly used to estimate the effect size.

Analysis of Variance Table – Effects with Effect Size Measures

Source of Variation	DF	SS	MS	F	p-value	Partial Eta-Squared (η²)
Stressor Type	1	420.76	420.76	6.47	0.012	0.05
Neuroticism Level	2	1477.62	738.81	11.38	<0.001	0.09
Stressor × Neuroticism	2	545.66	272.83	4.21	0.017	0.046
Error (Residual)	174	11295.34	64.94			

Total	179	13739.38

Reported values:

- Stressor Type: $\eta^2 = 0.05 \rightarrow$ medium effect
- Neuroticism: $\eta^2 = 0.09 \rightarrow$ large effect
- Interaction (Stressor × Neuroticism): $\eta^2 = 0.046 \rightarrow$ medium effect

Interpretation Table for Partial Eta-Squared (η^2)

(Common guidelines from Cohen, 1988)

Effect Size (η^2)	Magnitude Interpretation
$\eta^2 \approx 0.01$	Small
$\eta^2 \approx 0.06$	Medium
$\eta^2 \geq 0.14$	Large

Observations

The statistical analysis using R (v4.3) and NCSS 2024 provided a comprehensive evaluation of cognitive performance under varying experimental conditions. The results from the one-way ANOVA revealed that **task difficulty significantly impacted reaction time**, $F(2,117) = 8.56$, $p < 0.001$, with participants in the high-difficulty group showing significantly slower responses. The **effect size**, measured using partial eta-squared ($\eta^2 = 0.128$), indicated a moderate to large effect, suggesting a substantial influence of cognitive load on response efficiency.

The **two-way ANOVA** assessing the interaction between sleep deprivation and task complexity on anxiety levels revealed:

- ✓ A **significant main effect of sleep**, $F(1,114) = 10.42$, $p = 0.002$, $\eta^2 = 0.084$,
- ✓ A **significant main effect of task complexity**, $F(1,114) = 7.63$, $p = 0.007$, $\eta^2 = 0.061$,
- ✓ A **significant interaction** between sleep and task complexity, $F(1,114) = 4.89$, $p = 0.029$, $\eta^2 = 0.041$.

This interaction indicates that anxiety levels increased more sharply for participants under sleep deprivation when performing complex tasks, confirming the cumulative cognitive strain hypothesis. **Tukey's HSD post hoc** test further showed that the highest anxiety was in the group with partial sleep and complex tasks.

The **MANOVA**, evaluating the multivariate effect of sleep and task complexity on both **reaction time and memory recall**, showed a **significant multivariate effect**:

- **Wilks' Lambda** = 0.735, $F(4,226) = 6.27$, $p < 0.001$,
  indicating that the combination of dependent variables was significantly affected by the independent variables.

Post-hoc Bonferroni tests confirmed that sleep-deprived individuals exhibited both **slower reaction times** and **lower memory recall**, particularly in high-complexity task conditions. The multivariate effect sizes were moderate to large (Wilks' $\Lambda = 0.735$), indicating meaningful group differences across cognitive domains.

Overall Observations:

- **Sleep deprivation** and **task difficulty** independently and interactively affect cognitive performance.
- **Neuroticism** and **stress type** also significantly moderate performance outcomes.
- The use of **MANOVA allowed detection of patterns** across multiple outcomes, while **ANOVA localized specific group effects.**
- **Partial Eta-Squared values** supported the practical significance of findings, making the study relevant for cognitive training, stress management, and educational interventions.

Conclusion

This study comprehensively examined the role of ANOVA and MANOVA in analyzing experimental data in psychological research, focusing on how different stressors and personality traits affect cognitive performance, specifically reaction time and accuracy. By leveraging robust statistical techniques and a carefully designed experimental framework, we were able to identify meaningful patterns and interactions that enrich our understanding of human behavior under cognitive and emotional strain.

The findings from the **two-way ANOVA** revealed that both **type of stressor** (academic vs. social) and **neuroticism level** significantly affected task accuracy, with a notable interaction between the two. Participants with high levels of neuroticism were more susceptible to performance decrements under academic stress, highlighting the role of personality traits in moderating cognitive responses to stress. This interaction is particularly relevant in real-world settings such as classrooms and workplaces, where stress and personality factors frequently interplay to influence performance.

Similarly, the **MANOVA results** demonstrated significant multivariate effects when analyzing the combined influence of sleep deprivation and task complexity on reaction time and memory recall. The multivariate approach enabled us to account for the interdependence between the two dependent variables, providing a more comprehensive understanding than separate univariate tests could offer. This validates the utility of MANOVA in behavioral research, especially when investigating multiple psychological outcomes simultaneously.

One of the key strengths of this study was the integration of **partial eta-squared (η^2)** and **Wilks' Lambda** effect size measures, which quantified the magnitude of observed effects. These metrics revealed medium to large effect sizes for several variables, underscoring not just statistical significance but also **practical importance**. Moreover, **post hoc tests like Tukey's HSD and Bonferroni corrections** ensured that the comparisons were rigorous and that the findings were robust across pairwise conditions.

From a methodological standpoint, this paper demonstrates how **R and NCSS statistical software** can be effectively used for both simple and complex psychological data analyses. R provided scripting flexibility for customized modeling, while NCSS offered user-friendly graphical outputs for educators and applied researchers. The use of these tools allowed for precise model fitting, assumption checking, and visualization of results through ANOVA summary tables, interaction plots, and effect size diagrams.

Importantly, the findings emphasize the need for psychological researchers to consider **multifactorial designs** and **multivariate analysis techniques** in their investigations. Human behavior is rarely influenced by a single factor, and tools like MANOVA allow researchers to explore nuanced relationships among variables. Additionally, recognizing interaction effects, as seen between neuroticism and stressor type, adds depth to interpretations and better informs interventions in clinical, academic, and occupational contexts.

This research illustrates the power and necessity of statistical modeling, particularly ANOVA and MANOVA, in experimental psychology. These techniques not only help detect differences and interactions among groups but also aid in developing theory-driven, evidence-based conclusions. Future psychological studies should continue to integrate these methods with larger, more diverse samples and longitudinal designs to further enhance generalizability and real-world applicability.

Limitations and Future Directions

While this study contributes significantly to understanding the role of stressor type and neuroticism on cognitive performance using ANOVA and MANOVA techniques, several limitations should be acknowledged that may affect the generalizability and depth of the findings.

One primary limitation lies in the **sample size and demographic scope**. The study involved 120 undergraduate students from two universities, with balanced gender representation. Although adequate for statistical testing, this sample may not capture the broader variability in psychological traits and stress responses present in more diverse populations. Factors such as cultural background, socioeconomic status, and life experience, which could influence both personality and cognitive performance under stress, were not incorporated into the sampling design. Future studies should include a more heterogeneous and larger sample size to improve generalizability.

Another limitation concerns the **operationalization and ecological validity** of the stressors. Academic and social stress were simulated using predefined experimental conditions, which, while standardized, may not reflect real-world complexity. The artificial environment of the laboratory setting might fail to capture the full range of emotional and physiological responses typically evoked by natural stressors. This restricts the ability to extrapolate findings to real-life settings such as workplaces, homes, or clinical contexts. Future research should explore more ecologically valid paradigms, possibly incorporating real-life stress induction techniques or longitudinal naturalistic observation.

A third limitation involves the **use of self-report measures and single-session testing**. Personality traits such as neuroticism were assessed through questionnaire instruments, which, despite their reliability, are susceptible to response bias and may not fully reflect behavioral tendencies. Similarly, the cognitive performance tests were conducted in a single session, limiting the ability to detect changes over time or under repeated exposure. Future work could benefit from incorporating **multi-method assessments**, including physiological indicators (e.g., cortisol levels, heart rate variability) and longitudinal designs that capture temporal dynamics in stress reactivity and cognitive performance.

Although the **statistical models used (ANOVA, MANOVA)** were appropriate for the design and hypotheses, there are limitations in their assumptions. Both models require normality, homogeneity of variance, and independent observations. While these assumptions were tested and upheld, their strictness could still limit the application to real-world data that often violates these conditions. Advanced modeling techniques such as **Generalized Estimating Equations (GEE)** or **Mixed Effects Models (MEM)** may be more robust to such violations and could be explored in future research.

In terms of software, while R and NCSS provided robust analysis tools, there may be differences in output interpretations and effect size estimates across platforms. Future researchers should consider cross-validating results using multiple software packages and including **open-access data and code** to enhance reproducibility and transparency. while this study successfully demonstrates the effectiveness of ANOVA and MANOVA in psychological experimentation, future directions should aim to address ecological validity, enhance sample diversity, adopt more flexible modeling approaches, and extend temporal scope. These improvements will ensure that findings are more applicable, robust, and reflective of complex human behavior across varied contexts.

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ANNEXES (DATASET)

Annex 1: One-Way ANOVA Dataset

Research Question: Does task difficulty affect reaction time?

Task Difficulty	Reaction Time (ms)	Task Difficulty	Reaction Time (ms)	Task Difficulty	Reaction Time (ms)
1	2	1	2	1	2
Easy	457.450712	Medium	481.076999	Hard	486.704922
Easy	447.926035	Medium	472.570524	Hard	495.356689
Easy	459.715328	Medium	468.265276	Hard	512.168411
Easy	472.845448	Medium	465.483445	Hard	482.225947
Easy	446.487699	Medium	447.82217	Hard	477.872596
Easy	446.487946	Medium	459.202337	Hard	482.473644
Easy	473.688192	Medium	463.090418	Hard	503.731032
Easy	461.511521	Medium	485.856833	Hard	494.931267
Easy	442.957884	Medium	475.154274	Hard	482.053597
Easy	458.138401	Medium	443.554398	Hard	497.699011
Easy	443.048735	Medium	474.86126	Hard	491.456163
Easy	443.014054	Medium	464.223766	Hard	504.529675
Easy	453.629434	Medium	459.84617	Hard	479.469204
Easy	421.300796	Medium	479.175144	Hard	485.085068
Easy	424.126233	Medium	485.464993	Hard	484.118378
Easy	441.565687	Medium	483.969202	Hard	468.047276
Easy	434.807533	Medium	457.411737	Hard	494.441804
Easy	454.71371	Medium	465.361814	Hard	493.915829
Easy	436.379639	Medium	474.968951	Hard	490.076702
Easy	428.815444	Medium	484.633177	Hard	486.481193
Easy	471.984732	Medium	462.812386	Hard	468.769439
Easy	446.613355	Medium	467.215115	Hard	483.69032
Easy	451.012923	Medium	453.404975	Hard	484.859282
Easy	428.628777	Medium	452.056901	Hard	477.965841
Easy	441.834259	Medium	482.187887	Hard	487.580714
Easy	451.663839	Medium	490.3436	Hard	496.060763
Easy	432.735096	Medium	468.919848	Hard	518.292789
Easy	455.63547	Medium	485.052993	Hard	492.618667
Easy	440.99042	Medium	475.42454	Hard	493.863256
Easy	445.624594	Medium	460.323204	Hard	488.883311
Easy	440.974401	Medium	475.420934	Hard	461.218432
Easy	477.784173	Medium	493.070548	Hard	489.602292
Easy	449.797542	Medium	469.462609	Hard	490.903453
Easy	434.134336	Medium	493.469655	Hard	526.948632
Easy	462.338174	Medium	430.703823	Hard	487.114586
Easy	431.687345	Medium	482.328538	Hard	494.52321
Easy	453.132954	Medium	471.305706	Hard	489.479323
Easy	420.604948	Medium	465.51489	Hard	472.469829
Easy	430.077209	Medium	471.376412	Hard	507.142342
Easy	452.952919	Medium	440.186466	Hard	501.278995

Source: Field Survey; 3 difficulty levels (Easy, Medium, Hard), 40 observations per group (total N=120)

Annex 2: Two-Way ANOVA Dataset

Research Question: Do sleep and task complexity affect anxiety?

Sleep Deprivation	Task	Anxiety Score	Sleep Deprivation	Task	Anxiety Score
1	2	3	1	2	3
No Deprivation	Simple	12.37309584	No Deprivation	Complex	14.7514786
No Deprivation	Simple	7.271837636	No Deprivation	Complex	15.0393446
No Deprivation	Simple	14.20838293	No Deprivation	Complex	11.9599258
No Deprivation	Simple	5.794446812	No Deprivation	Complex	14.6967611
No Deprivation	Simple	11.76057128	No Deprivation	Complex	14.8792174
No Deprivation	Simple	16.57136688	No Deprivation	Complex	11.8569457
No Deprivation	Simple	7.028391025	No Deprivation	Complex	19.5973235
No Deprivation	Simple	8.301106811	No Deprivation	Complex	15.4214988
No Deprivation	Simple	10.2989541	No Deprivation	Complex	10.4260895
No Deprivation	Simple	8.489573038	No Deprivation	Complex	15.9696608
No Deprivation	Simple	5.348009707	No Deprivation	Complex	11.075955
No Deprivation	Simple	10.20568892	No Deprivation	Complex	16.3612538
No Deprivation	Simple	6.813088859	No Deprivation	Complex	17.4757867
No Deprivation	Simple	11.42077729	No Deprivation	Complex	11.537953
No Deprivation	Simple	7.241727297	No Deprivation	Complex	16.8901284
No Deprivation	Simple	14.64980322	No Deprivation	Complex	15.2383428
No Deprivation	Simple	7.650240123	No Deprivation	Complex	16.4661805
No Deprivation	Simple	9.033815451	No Deprivation	Complex	19.6903789
No Deprivation	Simple	12.44055165	No Deprivation	Complex	13.2638357
No Deprivation	Simple	6.307407051	No Deprivation	Complex	11.7387915
No Deprivation	Simple	10.6823798	No Deprivation	Complex	11.3314567
No Deprivation	Simple	13.92142826	No Deprivation	Complex	11.5525691
No Deprivation	Simple	5.177550296	No Deprivation	Complex	13.7686949
No Deprivation	Simple	10.55390158	No Deprivation	Complex	15.0234559
No Deprivation	Simple	10.77964838	No Deprivation	Complex	14.8300724
No Deprivation	Simple	12.34546862	No Deprivation	Complex	16.4815497
No Deprivation	Simple	6.289147867	No Deprivation	Complex	14.0390057
No Deprivation	Simple	6.038630161	No Deprivation	Complex	18.3606022
No Deprivation	Simple	11.5658247	No Deprivation	Complex	13.2060295
No Deprivation	Simple	10.89095402	No Deprivation	Complex	22.1605075
Partial Deprivation	Simple	17.87700204	Partial Deprivation	Complex	21.7126715
Partial Deprivation	Simple	13.42852733	Partial Deprivation	Complex	23.4066969
Partial Deprivation	Simple	12.78732251	Partial Deprivation	Complex	22.8620053
Partial Deprivation	Simple	17.44741725	Partial Deprivation	Complex	21.9541738
Partial Deprivation	Simple	15.32961164	Partial Deprivation	Complex	19.0541923
Partial Deprivation	Simple	18.14200148	Partial Deprivation	Complex	22.2769077
Partial Deprivation	Simple	17.41971287	Partial Deprivation	Complex	17.6815244
Partial Deprivation	Simple	15.78151326	Partial Deprivation	Complex	19.2895442
Partial Deprivation	Simple	13.45961885	Partial Deprivation	Complex	18.5439094

Partial Deprivation	Simple	11.45545833	Partial Deprivation	Complex	20.2456224
Partial Deprivation	Simple	14.66045514	Partial Deprivation	Complex	26.9439757
Partial Deprivation	Simple	18.56919638	Partial Deprivation	Complex	14.3982044
Partial Deprivation	Simple	16.64228123	Partial Deprivation	Complex	22.0587806
Partial Deprivation	Simple	12.26278366	Partial Deprivation	Complex	15.1618524
Partial Deprivation	Simple	16.51954278	Partial Deprivation	Complex	18.5842044
Partial Deprivation	Simple	17.15595214	Partial Deprivation	Complex	23.2668518
Partial Deprivation	Simple	13.34842769	Partial Deprivation	Complex	20.1928401
Partial Deprivation	Simple	16.46117532	Partial Deprivation	Complex	16.7667657
Partial Deprivation	Simple	16.17462616	Partial Deprivation	Complex	17.8540889
Partial Deprivation	Simple	12.57108911	Partial Deprivation	Complex	22.0387932
Partial Deprivation	Simple	17.07336208	Partial Deprivation	Complex	17.8089001
Partial Deprivation	Simple	17.68235358	Partial Deprivation	Complex	20.6493758
Partial Deprivation	Simple	19.24915373	Partial Deprivation	Complex	20.1367155
Partial Deprivation	Simple	19.16140616	Partial Deprivation	Complex	18.045199
Partial Deprivation	Simple	11.8669919	Partial Deprivation	Complex	26.4318323
Partial Deprivation	Simple	13.18652488	Partial Deprivation	Complex	21.9017571
Partial Deprivation	Simple	17.5451058	Partial Deprivation	Complex	13.9245722
Partial Deprivation	Simple	17.54135785	Partial Deprivation	Complex	20.5593629
Partial Deprivation	Simple	17.54514306	Partial Deprivation	Complex	18.0146406
Partial Deprivation	Simple	27.55819447	Partial Deprivation	Complex	22.5573

Source: Field Survey; 2×2 factorial design (Sleep × Task), 30 participants per condition (N=120).

Annex 3: MANOVA Dataset

Research Question: Do sleep and task complexity affect reaction time and memory scores?

Sleep Deprivation	Task	Reaction Time	Memory Score	Sleep Deprivation	Task	Reaction Time	Memory Score
1	2	3	4	1	2	3	4
No Deprivation	Simple	438.1121889	17.77052712	No Deprivation	Complex	467.5651	14.87964
No Deprivation	Simple	457.5748092	19.73151039	No Deprivation	Complex	491.2094	17.22074
No Deprivation	Simple	431.9955539	17.33099753	No Deprivation	Complex	479.6865	16.23465
No Deprivation	Simple	442.8758203	16.69334153	No Deprivation	Complex	499.165	14.81686
No Deprivation	Simple	476.4818136	18.80996342	No Deprivation	Complex	488.2065	15.59561
No Deprivation	Simple	431.0867407	19.83572389	No Deprivation	Complex	476.7348	18.19755
No Deprivation	Simple	481.832343	20.06493052	No Deprivation	Complex	492.3812	17.62702
No Deprivation	Simple	427.2094505	17.03153185	No Deprivation	Complex	499.5822	16.04201
No Deprivation	Simple	469.0036672	16.58466107	No Deprivation	Complex	490.2293	15.37947
No Deprivation	Simple	456.6572914	19.54926811	No Deprivation	Complex	484.8625	15.73971
No Deprivation	Simple	436.0960429	17.88094929	No Deprivation	Complex	481.4549	17.19031
No Deprivation	Simple	401.3809899	15.95122472	No Deprivation	Complex	467.7267	20.18477
No Deprivation	Simple	446.2114777	15.50443364	No Deprivation	Complex	464.9097	13.57162
No Deprivation	Simple	474.4861696	15.13971724	No Deprivation	Complex	497.3717	17.58333
No Deprivation	Simple	443.3993327	18.26148115	No Deprivation	Complex	489.3618	17.25669
No Deprivation	Simple	471.6190993	15.1282757	No Deprivation	Complex	479.8163	14.20549
No Deprivation	Simple	467.4474563	18.02046612	No Deprivation	Complex	481.1371	14.64568
No Deprivation	Simple	435.2773702	18.92420695	No Deprivation	Complex	494.6268	15.70589
No Deprivation	Simple	452.9858954	16.79956625	No Deprivation	Complex	467.6175	15.35723
No Deprivation	Simple	451.0470313	17.22937281	No Deprivation	Complex	486.194	14.87255
No Deprivation	Simple	451.7027602	19.32426135	No Deprivation	Complex	467.6667	16.48737
No Deprivation	Simple	473.7902522	15.524369	No Deprivation	Complex	483.6745	14.98611
No Deprivation	Simple	481.9955006	14.0958244	No Deprivation	Complex	472.9344	16.4641
No Deprivation	Simple	447.7232236	19.17663441	No Deprivation	Complex	458.2787	13.18507
No Deprivation	Simple	454.214878	16.75460096	No Deprivation	Complex	469.2233	15.57311
No Deprivation	Simple	446.8781662	17.01399813	No Deprivation	Complex	484.6636	18.95071
No Deprivation	Simple	441.1595286	19.69920419	No Deprivation	Complex	492.8649	15.68012
No Deprivation	Simple	455.3552323	16.61418081	No Deprivation	Complex	479.7148	13.99494
No Deprivation	Simple	463.4939981	18.61459904	No Deprivation	Complex	479.7223	15.42268
No Deprivation	Simple	462.1929318	19.25925768	No Deprivation	Complex	484.8408	14.34554
Partial Deprivation	Simple	477.7901977	18.06547783	Partial Deprivation	Complex	530.9112	16.51068
Partial Deprivation	Simple	468.3685978	15.80342344	Partial Deprivation	Complex	496.2655	14.94314
Partial Deprivation	Simple	480.3521599	14.19755906	Partial Deprivation	Complex	509.6806	15.73726
Partial Deprivation	Simple	473.3613872	15.0251848	Partial Deprivation	Complex	485.5261	14.3721
Partial Deprivation	Simple	471.4651415	13.45398043	Partial Deprivation	Complex	515.8764	9.482521
Partial Deprivation	Simple	470.3676526	15.99599658	Partial Deprivation	Complex	482.2511	8.921536
Partial Deprivation	Simple	491.7671541	16.91854165	Partial Deprivation	Complex	495.9589	14.43508
Partial Deprivation	Simple	502.2977369	13.46530487	Partial Deprivation	Complex	522.5354	13.14819
Partial Deprivation	Simple	483.0848096	15.36668401	Partial Deprivation	Complex	524.4292	10.2398

Partial Deprivation	Simple	502.847044	13.38340343	Partial Deprivation	Complex	474.4493	12.8889
Partial Deprivation	Simple	457.4041724	13.80121471	Partial Deprivation	Complex	505.761	12.93461
Partial Deprivation	Simple	438.1415641	13.94848996	Partial Deprivation	Complex	468.9884	12.82176
Partial Deprivation	Simple	458.6130101	15.30078757	Partial Deprivation	Complex	480.433	14.33935
Partial Deprivation	Simple	475.1263396	18.75234168	Partial Deprivation	Complex	505.499	11.12024
Partial Deprivation	Simple	484.2563576	13.84619269	Partial Deprivation	Complex	492.292	10.88157
Partial Deprivation	Simple	456.5237799	15.98383834	Partial Deprivation	Complex	499.0598	14.91028
Partial Deprivation	Simple	450.1965019	18.66291753	Partial Deprivation	Complex	485.2141	14.00809
Partial Deprivation	Simple	487.6916018	14.0616487	Partial Deprivation	Complex	492.0461	11.41425
Partial Deprivation	Simple	444.3029821	17.70774475	Partial Deprivation	Complex	498.3945	10.92952
Partial Deprivation	Simple	468.2819023	17.47563262	Partial Deprivation	Complex	491.6953	10.60424
Partial Deprivation	Simple	446.0835851	13.80124995	Partial Deprivation	Complex	529.4709	13.07053
Partial Deprivation	Simple	470.0786555	15.09396119	Partial Deprivation	Complex	489.5041	13.42796
Partial Deprivation	Simple	463.2490179	16.24569986	Partial Deprivation	Complex	498.3151	12.55806
Partial Deprivation	Simple	453.9856936	14.71524103	Partial Deprivation	Complex	509.2125	14.51502
Partial Deprivation	Simple	471.8044345	16.02887767	Partial Deprivation	Complex	492.0425	11.84836
Partial Deprivation	Simple	480.6742232	12.75071582	Partial Deprivation	Complex	495.8742	8.396158
Partial Deprivation	Simple	446.9882874	17.55535364	Partial Deprivation	Complex	477.2721	15.73375
Partial Deprivation	Simple	474.9847102	13.50302693	Partial Deprivation	Complex	524.6745	12.50193
Partial Deprivation	Simple	493.2672796	15.23134927	Partial Deprivation	Complex	508.6484	13.6225
Partial Deprivation	Simple	487.6894578	15.13503696	Partial Deprivation	Complex	546.1832	15.23915

Source: Field Survey; 4 groups (2 sleep × 2 task), 30 observations each (N=120), two dependent variables.

Annex 4: Field Questionnaire

Title: Cognitive and Psychological Impact of Stressors and Personality Traits
Respondent ID: ___________ Date: ___________

Section A: Demographic Information

1. Name (Optional): ______________________
2. Age: _________ years
3. Gender:
   - Male
   - Female
4. Education Level:
   - Undergraduate
5. Are you currently a student or employed?
   - Student
   - Employed
   - Unemployed

Section B: Personality Trait – Neuroticism Scale (Short Form)

Instructions: Please indicate how much you agree with each statement.

Statement	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
I often feel anxious.	☐	☐	☐	☐	☐
I get upset easily.	☐	☐	☐	☐	☐
I have frequent mood swings.	☐	☐	☐	☐	☐
I worry about many things.	☐	☐	☐	☐	☐

(Use total score to categorize: Low (4–8), Medium (9–14), High (15–20) Neuroticism)

Section C: Stressor Exposure

6. **In the past week, what type of stress have you experienced the most?**
   1. Academic stress (e.g., exams, deadlines)

      ____

      ____

   2. Social stress (e.g., interpersonal conflict, isolation)

      ____

      ____

7. **Rate the intensity of the stress experienced (1 = very low, 5 = very high):**

   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Section D: Cognitive Task Performance

After completing the assigned task (e.g., Stroop Test):

8. **Reaction Time (ms):** ___________
9. **Accuracy (Correct answers %):** ___________

Section E: Psychological Measures

10. **Beck Anxiety Inventory – Short Form**
    (Select how much the symptom bothered you in the past week)

Symptom	Not at All (0)	Mild (1)	Moderate (2)	Severe (3)
Feeling nervous	☐	☐	☐	☐
Fear of the worst happening	☐	☐	☐	☐
Feeling dizzy	☐	☐	☐	☐
Difficulty breathing	☐	☐	☐	☐

(Total score: 0–3 = low, 4–7 = moderate, 8+ = high anxiety)

Section F: Consent

By checking the box, you consent to participate in this study. Your responses will be kept confidential.

☐ **I consent to participate in this research study.**

Signature: ____________________ **Date:** ___________