IJMSSSR
International Journal of Management studies and Social Science Research
A Bi-Monthly, Peer-Reviewed, Open-Access Journal
2026 Vol. 08, Issue 04
ISSN: 2582-0265
www.ijmsssr.org

RESEARCH ARTICLE

Integrating ANOVA and Logistic Regression for Treatment Comparison: A Methodological Illustration with Simulated Data

Wan-Chen Wang[1]*, Maria de Fátima Alves de Pina[2,3], Maria Helena de Aguiar Pereira e Pestana[4,5], Yu-Tso Liu[1]

1 Department of Marketing, Feng Chia University, Taichung, Taiwan, Republic of China
2 ISLA Santarém, Santarém, Portugal
3 ISR-UC – Institute of Systems and Robotics, University of Coimbra, Coimbra, Portugal
4 Department of Quantitative Methods, ISCTE-Instituto Universitário de Lisboa, Lisbon, Portugal
5 CINTESIS@RISE – Health Research Network, University of Porto, Porto, Portugal

ORCID Identifiers
Wan-Chen Wang: https://orcid.org/0000-0003-4709-6831
Maria de Fátima Alves de Pina: https://orcid.org/0000-0003-3738-1153
Maria Helena de Aguiar Pereira e Pestana: https://orcid.org/0000-0003-3760-8178
Yu-Tso Liu: https://orcid.org/0009-0008-6387-2603

Corresponding Author
Wan-Chen Wang
Department of Marketing, Feng Chia University
No. 100, Wenhwa Rd., Seatwen, Xitun District
Taichung City 40724, Taiwan, Republic of China

ABSTRACT

Anxiety disorders impair daily functioning and well-being. CBT and MBCT are established treatments whose comparative effectiveness is often examined through a single analytic lens. This didactic study uses simulated data ($N = 60$; CBT $n = 30$; MBCT $n = 30$) to illustrate complementary statistical approaches to between-group differences in post-treatment anxiety, assessed by the Beck Anxiety Inventory (BAI). One-way ANOVA indicated a strong group effect, $F(1, 58) = 24.8$, $p = 6.07\times10^{-6}$, Cohen's $d = 1.29$, with MBCT showing lower anxiety ($M = 18.5$, $SD = 4.9$) than CBT ($M = 25.0$, $SD = 5.2$). Binary logistic regression showed each one-point BAI increase was associated with 23% lower odds of MBCT membership ($OR = 0.77$), with good discrimination ($AUC = 0.819$) and 76.7% accuracy. These analyses demonstrate that significance testing, effect-size estimation, and classification performance answer complementary questions. Data are fully simulated; findings are not intended for clinical generalization.

Keywords: *Cognitive-Behavioral Therapy, Mindfulness-Based Cognitive Therapy, Beck Anxiety Inventory, simulated data, anxiety*

ARTICLE INFO

Received:	[23/07/2026]
Accepted:	[10/08/2026]
Published:	[26/08/2026]
Issue Period:	July – August 2026 (Bi-Monthly)

DOI: https://doi.org/10.56293/IJMSSSR.2026.6326

Introduction

Anxiety disorders represent a significant and growing public health challenge, affecting well-being, productivity, and overall quality of life (Szuhany & Simon, 2022). Among empirically supported psychological interventions, Cognitive-Behavioral Therapy (CBT) and Mindfulness-Based Cognitive Therapy (MBCT) are widely implemented and extensively studied (Li et al., 2021). CBT targets maladaptive cognitions and behaviors that maintain anxiety, whereas MBCT integrates mindfulness practices to cultivate present-moment awareness and acceptance, thereby reducing habitual negative thought cycles. Across both approaches, standardized instruments such as the Beck Anxiety Inventory (BAI) provide quantitative indices to assess symptom severity and monitor therapeutic change.

Although the efficacy of both CBT and MBCT in reducing anxiety symptoms has been documented (Carpenter et al., 2018; Kuyken et al., 2016), questions remain regarding their relative impact and how best to quantify and interpret between-group differences. In applied research, one-way analysis of variance (ANOVA) is commonly used to test mean differences in continuous outcomes across treatment conditions. However, reliance on group means alone may obscure additional inferential perspectives—particularly when the same data can also be approached from a discrimination or classification standpoint (Keselman et al., 2001).

When the explanatory variable is dichotomous (e.g., therapy group) and the outcome is continuous (e.g., anxiety score), two complementary analytical perspectives can be informative. One-way ANOVA evaluates whether average outcomes differ between groups, whereas binary logistic regression addresses the inverse relationship by modelling how continuous outcomes relate to the probability of belonging to one group versus the other (Tabachnick & Fidell, 2001). Importantly, valid ANOVA inference depends on key assumptions—independence of observations, approximate within-group normality, and homogeneity of variances (Lix & Keselman, 1996)—and, when these conditions are not met due to outliers or non-normality, robust alternatives or transformations may be warranted (Lix & Keselman, 1996; Field & Wilcox, 2017; Hosmer et al., 2013).

Accordingly, the present paper adopts a didactic and methodological focus by illustrating the joint use of one-way ANOVA and binary logistic regression to compare CBT and MBCT using the BAI as the outcome measure. Specifically, we use a fully simulated dataset structured to resemble plausible post-treatment BAI scores (BAI_Post) across CBT and MBCT groups, demonstrating how mean-difference testing and classification-oriented modelling yield distinct yet complementary insights into treatment comparisons. Because the data are simulated and restricted to post-treatment outcomes, ethical approval was not required, and results are not intended for clinical generalisation (Committee on Publication Ethics [COPE] Council, n.d.).

The remainder of this paper is organized as follows. The next section (Therapy Methods) briefly introduces CBT, MBCT, and the use of the BAI to contextualize the simulated comparison. The Methodology section details the simulation design, data-generation rationale, sociodemographic structure, outcome definition, and the statistical procedures employed (descriptive statistics, one-way ANOVA, and binary logistic regression). The Results present the simulated sample characteristics, between-group comparisons of post-treatment anxiety, model-based discrimination metrics, and an optional adjusted logistic model for didactic purposes. The Discussion interprets these findings from a methodological perspective, synthesizing the complementary insights offered by mean-difference testing and classification modelling. The Limitations and Conclusion clarify the boundaries of interpretation, emphasising that all results are simulation-based and intended solely for instructional illustration rather than clinical generalisation.

Therapy Methods

The Beck Anxiety Inventory (BAI) is a widely used self-report instrument designed to measure the severity of anxiety symptoms. In both CBT and MBCT, the BAI is used to quantify anxiety, monitor symptom change, and support treatment planning. In this study, simulated post-treatment BAI scores were used to illustrate differences between the two therapeutic approaches.

Interventions (CBT and MBCT)

Two therapy conditions were considered: Cognitive-Behavioral Therapy (CBT) and Mindfulness-Based Cognitive Therapy (MBCT). CBT is a structured, goal-oriented intervention targeting maladaptive cognitions and behaviors linked to anxiety, commonly using strategies such as cognitive restructuring, exposure-based techniques, and behavioral experiments (Carpenter et al., 2018). MBCT integrates mindfulness practice with cognitive-behavioral elements, emphasizing present-moment awareness, acceptance, and reduced reactivity to distressing internal experiences (Kuyken et al., 2016). In the present paper, these interventions are described to contextualize a didactic, simulated comparison of post-treatment anxiety outcomes rather than to report an actual clinical trial.

Outcome Measure (Beck Anxiety Inventory)

Anxiety symptoms were operationalized using the Beck Anxiety Inventory (BAI), a standardized self-report measure of anxiety symptom severity (Beck et al., 1988). In routine clinical and research contexts, the BAI can be administered at treatment entry to quantify initial symptom burden, repeated during treatment to monitor change, and administered post-treatment to evaluate outcome. In this simulated example, the analyses focus on post-treatment BAI scores (BAI_Post) as the continuous outcome used to compare therapy groups and to illustrate complementary statistical perspectives.

BAI Use Across Both Therapies

In both CBT and MBCT, standardized symptom monitoring can support: (i) quantifying initial severity and goal setting; (ii) tracking symptom trajectories over time; and (iii) summarizing end-of-treatment outcome (Beck et al., 1988). Conceptually, this shared measurement strategy facilitates transparent comparisons across therapeutic approaches while keeping the outcome definition constant.

Comparative Rationale and Analytic Perspective

When comparing a dichotomous explanatory variable (therapy group) on a continuous outcome (BAI_Post), one-way ANOVA provides a mean-difference perspective, whereas binary logistic regression provides a classification-oriented perspective by modelling how anxiety scores relate to group membership (Tabachnick & Fidell, 2001). This paper uses both approaches to illustrate how different statistical summaries can yield convergent yet non-identical interpretations of the same dataset.

Ethics Statement (Simulated Data)

Because the dataset is fully simulated and contains no information from real participants, ethical approval and informed consent were not required, and results are not intended to be generalized to clinical settings. Consistent with publication-ethics guidance, studies should include either ethics approval details or a clear statement explaining why approval was not required.

Methodology

This paper presents a didactic, simulation-based study designed to illustrate how complementary statistical approaches—one-way ANOVA and binary logistic regression—can be applied to compare two therapeutic conditions (CBT vs. MBCT) using a continuous anxiety outcome. No real participants were involved; all data were synthetically generated for methodological demonstration. A reproducible Python script and the exact package versions are provided in the Supplementary Materials to facilitate verification and reuse.

Study Design

A quantitative, simulation-based design was used to generate a balanced sample representing two therapy conditions: CBT and MBCT. The simulated dataset contains 60 synthetic cases, with 30 assigned to each group, allowing for controlled comparisons under idealized conditions. Assignment was created algorithmically to ensure equal group size. The design objective is methodological (didactic), not clinical: outcome differences were encoded at the simulation stage to demonstrate how mean-difference testing and classification modeling provide complementary insights when applied to the same continuous endpoint (post-treatment BAI).

Simulated Data Generation and Rationale

In this didactic simulation, we illustrate the complementary use of one-way ANOVA and binary logistic regression using a fully synthetic dataset ($n = 60$; CBT $n = 30$; MBCT $n = 30$). Post-treatment anxiety (BAI_Post) was generated from normal distributions to reflect a plausible clinical-like separation between groups (CBT ~ Normal (25.3, 5.2); MBCT ~ Normal (18.7, 4.8)), with values truncated to the admissible BAI range [0, 63] to preserve scoring realism. Sociodemographic variables (sex, education, employment status, marital status) were also simulated to yield broadly comparable group profiles. Analyses were performed in Python (NumPy/SciPy/stats models/scikit-learn).

All variables were simulated for didactic purposes. Post-treatment anxiety was operationalized as BAI_Post and generated within the Beck Anxiety Inventory total-score range (0–63), commonly interpreted using severity bands (minimal 0–7, mild 8–15, moderate 16–25, severe 26–63).

To resemble a clinical sample, parameter values were chosen so that many post-treatment scores remained in the moderate-to-severe range, while still allowing meaningful improvement and overlap between groups. Specifically, the simulated MBCT group was assigned a lower post-treatment mean than the CBT group to create a plausible between-group contrast suitable for illustrating effect estimation (mean differences and Cohen’s d) and discrimination/classification (logistic regression, AUC).

Sociodemographic variables (sex, education, employment, marital status) were generated to reflect reasonable distributions typically reported in applied samples and were approximately balanced across groups to minimize spurious group differences unrelated to the didactic objective. All simulated values were restricted to admissible categories (categorical variables) and to the valid BAI scoring range (BAI_Post). Because the data were drawn from finite random samples, observed sample means may differ slightly from the specified population parameters; this is expected and reflects natural sampling variability.

Table 1 presents the descriptive sociodemographic profile of the simulated dataset ($N = 60$), stratified by therapy group. Values are presented as n (column %).

Table 1. Simulated Socio-Demographic Characteristics

Characteristic	CBT (n = 30)	MBCT (n = 30)	Total (n = 60)
Sex			

Male	15 (50%)	14 (46.7%)	29 (48.3%)
Female	15 (50%)	16 (53.3%)	31 (51.7%)
Education Level			
High school	9 (30%)	6 (20%)	15 (25%)
Bachelor's degree	12 (40%)	13 (43.3%)	25 (41.7%)
Master's degree	4 (13.3%)	9 (30%)	13 (21.7%)
Doctorate	5 (16.7%)	2 (6.7%)	7 (11.7%)
Employment Status			
Employed	18 (60%)	23 (76.7%)	41 (68.3%)
Unemployed	7 (23.3%)	2 (6.7%)	9 (15%)
Student	5 (16.7%)	5 (16.7%)	10 (16.7%)
Marital Status			
Single	7 (23.3%)	16 (53.3%)	23 (38.3%)
Married/common law union	20 (66.7%)	11 (36.7%)	31 (51.7%)
Divorced	3 (10%)	3 (10%)	6 (10%)

Note. Values are n (column %). CBT = Cognitive-Behavioral Therapy; MBCT = Mindfulness-Based Cognitive Therapy.

Procedure

Because this is a simulated study, no therapeutic procedures were administered and no ethical approval or informed consent were required. Rather than modelling the temporal trajectory of therapy, the dataset includes only post-treatment anxiety scores (BAI_Post), permitting clear demonstration of two complementary analytical techniques.

Measures

Beck Anxiety Inventory (BAI_Post)

The Beck Anxiety Inventory (BAI) is a validated measure of anxiety symptom severity (Beck et al., 1988). In this study, only post-treatment scores were simulated. Values were generated to approximate plausible clinical distributions expected in CBT and MBCT interventions, with MBCT designed to have a slightly lower mean to allow demonstration of between-group differences and model-based discrimination.

Statistical Analysis

Descriptive Statistics.

Means, standard deviations, and confidence intervals were computed for BAI_Post in both simulated groups to summarize central tendency and dispersion.

One-Way ANOVA.

A one-way ANOVA was conducted to compare mean post-treatment anxiety scores (BAI_Post) between the two simulated therapy groups. Assumptions of normality and homogeneity of variances were evaluated to illustrate standard analytical practice.

Binary Logistic Regression.

Logistic regression modelled therapy-group membership (CBT = 0, MBCT = 1) as a function of BAI_Post, emphasizing a classification perspective rather than a real assignment mechanism. Model performance was summarized using discrimination indices (e.g., AUC) and classification accuracy, with goodness-of-fit assessed using standard diagnostics (e.g., calibration or Hosmer–Lemeshow-type checks, where applicable).

Software.
All analyses were conducted using Python 3.11/3.12, using standard scientific libraries for data handling and statistical modelling (e.g., pandas, SciPy, statsmodels, and scikit-learn for AUC/accuracy).

Illustrative Case Example (Didactic Purpose)
To reinforce understanding, the simulated dataset is treated as an illustrative case example demonstrating how therapy-group comparisons can be analyzed. It does not represent actual treatment effects or real participants, and findings are not intended for clinical generalization.

Simulated CBT vs. MBCT Anxiety Dataset: Tables and Key Results

The simulated sample (Table 1) was balanced on sex (CBT: 50% female; MBCT: 53.3% female). Education profiles were broadly comparable across groups (Bachelor's: 40.0% vs. 43.3%; Master's: 13.3% vs. 30.0%; High School: 30.0% vs. 20.0%; Doctorate: 16.7% vs. 6.7%). Employment was somewhat higher in MBCT (76.7% vs. 60.0%), while marital status showed more Married/Common Law Union in CBT (66.7% vs. 36.7%) and more Single in MBCT (53.3% vs. 23.3%). These patterns are consistent with the didactic goal of broadly comparable groups with small, realistic imbalances typical of clinical-like scenarios. Analyses below focus on unadjusted between-group comparisons of BAI_Post; were this a real-world trial, adjusted models could be considered to account for covariates.

MBCT (Table 2) shows lower post-treatment anxiety than CBT by 6.5 points on average; the 95% CI excludes 0, indicating a statistically and practically meaningful difference. Group CIs (CBT ≈ [23.0, 26.9]; MBCT ≈ [16.6, 20.3]) show acceptable precision for n = 30 per arm.

Table 2. Post-Treatment Anxiety (BAI_Post) by Therapy Group

Therapy	N	M (SD)	95% CI LL	95% CI UL
CBT	30	25.0 (5.2)	23.0	26.9
MBCT	30	18.5 (4.9)	16.6	20.3
Mean difference (CBT − MBCT)			6.5 points	(95% CI: 3.9 to 9.1)

Note. M = mean; SD = standard deviation; CI = confidence interval; LL = lower limit; UL = upper limit.

Figure 1 shows box-and-whisker plots overlaid with mirrored kernel densities and jittered points to display distributional shape and individual observations. Overlaid histograms/densities show MBCT scores shifted lower than CBT with realistic overlap. This aligns with the mean difference (CBT − MBCT) ≈ 6.5 points (95% CI 3.9–9.1) and Cohen's d ≈ 1.29 (large) in Table 3, while explaining why the logistic model yields good but not perfect discrimination (AUC ≈ 0.82; accuracy ≈ 76.7%). The y-axis reflects the valid BAI range (0–63), consistent with standard scoring conventions.

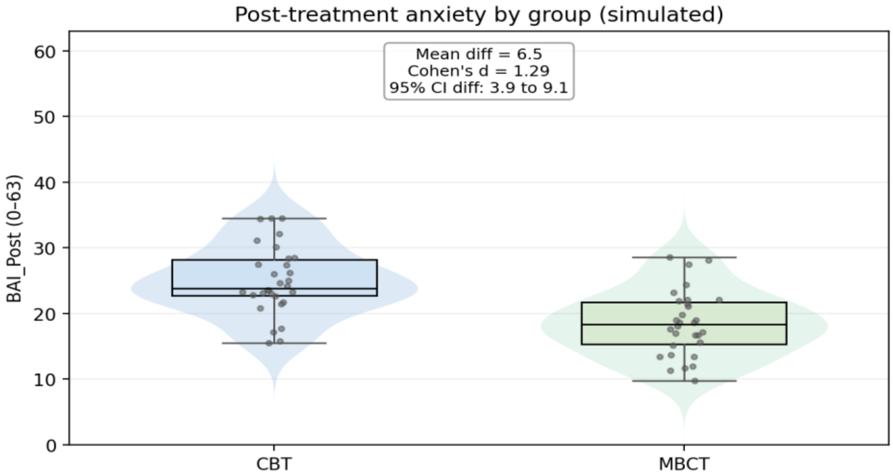

Figure 1. *Distribution of post-treatment anxiety by therapy group (simulated).*

ANOVA (Table 3) confirms a statistically significant between-group difference in BAI_Post. The effect size is large (d ≈ 1.29), implying a substantial separation of post-treatment anxiety distributions. ANOVA addresses the "Do the means differ?" question, whereas d quantifies "How much?"

Table 3. ANOVA and Effect Size

Results
One-way ANOVA: $F(1, 58) = 24.8$, $p = 6.07\times10^{-6}$
Cohen's d (CBT vs. MBCT) = 1.29 (positive indicates higher anxiety in CBT)

Note. A large effect size (d ≥ 0.80) indicates substantial separation of post-treatment anxiety distributions between groups.

With each +1 point increase in BAI_Post (Table 4, Figure 2), the odds of belonging to the MBCT group decrease by approximately 23% (OR = 0.77); equivalently, a −1 point decrease is associated with approximately 29% higher odds of MBCT (1/0.77 ≈ 1.29). The 95% CI for OR excludes 1, supporting a statistically reliable association. Discriminative ability is good (AUC ≈ 0.82), and the simple 0.50 cutoff attains approximately 76.7% accuracy.

Table 4. Logistic Regression (MBCT = 1 vs. CBT = 0)

Logistic Regression (MBCT = 1 vs. CBT = 0)
Coefficient (BAI_Post): B = −0.257 (SE = 0.071), OR = 0.77 (95% CI 0.67–0.89), $p = 2.96\times10^{-4}$
Discrimination: AUC = 0.819. Accuracy at 0.50 threshold = 76.7%
Confusion matrix (threshold = 0.50): TN = 24, FP = 6, FN = 8, TP = 22

Note. OR = odds ratio; CI = confidence interval; AUC = area under the ROC curve; TN = true negative; FP = false positive; FN = false negative; TP = true positive.

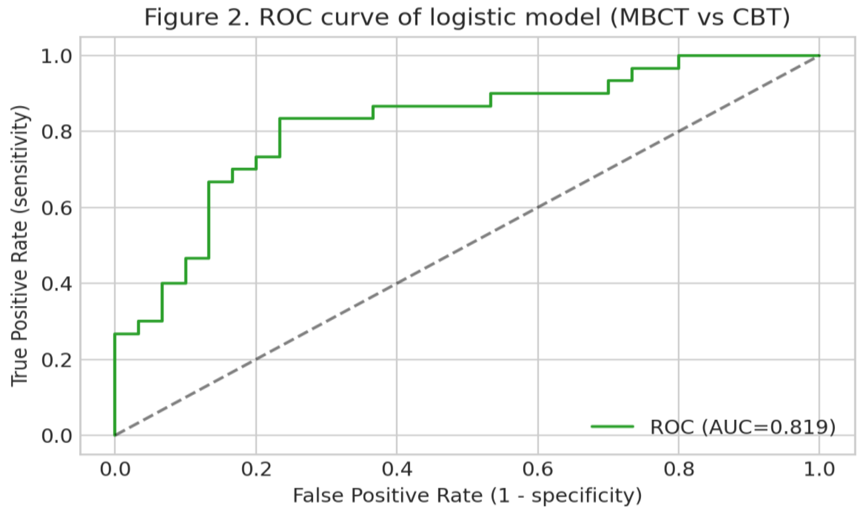

Figure 2. *ROC curve of logistic model (MBCT vs. CBT).*

Both analyses matter: ANOVA with Cohen's d provides evidence of a mean difference and its magnitude, whereas the logistic model with AUC/accuracy offers a classification view of the same relationship, showing how well a continuous outcome (BAI_Post) can separate the two groups. Joint interpretation emphasizes that significance, effect size, and classification performance answer different, complementary questions about the same data.

Adjusted Logistic Model (Optional, Didactic)

To illustrate how one might add a simple covariate while keeping the focus on the didactic nature of the simulation, a logistic regression was fit for MBCT (1) vs. CBT (0) with BAI_Post plus Marital Status (reference = Married/Common Law Union). Results (Table 5) are illustrative only; they are not intended to generalize clinically. BAI_Post remains a strong discriminator after adjustment. Single shows a borderline increase in the odds of belonging to MBCT vs. Married (wide CI, consistent with limited sample size and simulated imbalances). The AUC improvement (≈ 0.82 → ≈ 0.86) illustrates how a covariate can incrementally improve discrimination.

Table 5. Adjusted Logistic Model

Variable	B	SE	p	OR	95% CI (OR)
BAI_Post	−0.269	0.079	.001	0.76	0.66–0.89
Divorced (vs. Married)	−0.522	1.116	.64	0.59	0.07–5.29
Single (vs. Married)	1.367	0.725	.059	3.92	0.95–16.27

Note. Discrimination: AUC ≈ 0.857; accuracy = 81.7% (threshold = 0.50). Confusion matrix: TN = 26, FP = 4, FN = 7, TP = 23.

Discussion, Limitations, and Conclusion

Discussion

This didactic simulation illustrates how complementary statistical perspectives can sharpen inferences about differences between CBT and MBCT on post-treatment anxiety as measured by the BAI (Beck et al., 1988). Consistent with syntheses documenting the efficacy of CBT and mindfulness-based approaches in anxiety and mood conditions (Carpenter et al., 2018; Hofmann et al., 2010; Khoury et al., 2013), the simulated data showed lower post-treatment BAI scores in the MBCT group relative to CBT. Interpreting these patterns through both one-way ANOVA (mean differences and effect size) and binary logistic regression (odds ratios and discrimination) underscores that significance tests, effect-size estimation, and classification performance address related but distinct inferential questions (Cohen, 1988; Tabachnick & Fidell, 2001; Hosmer et al., 2013).

Methodologically, ANOVA provides a principled test of average group differences under assumptions of independent observations, approximate within-group normality, and homogeneity of variances; when these assumptions are doubtful—for example, due to outliers or skew—robust procedures or transformations should be considered (Lix & Keselman, 1996; Keselman et al., 2001; Field & Wilcox, 2017). Logistic regression complements this view by modelling how continuous anxiety scores separate groups, yielding interpretable measures such as odds ratios and AUC that speak to classification performance (Hosmer et al., 2013; Tabachnick & Fidell, 2001). Taken together, the dual perspective reduces over-reliance on a single summary metric and improves didactic clarity when teaching comparative analyses.

From a substantive standpoint, the simulated advantage for MBCT accords with meta-analytic evidence that mindfulness-based therapies can reduce anxiety and depressive symptoms (Hofmann et al., 2010; Khoury et al., 2013), while acknowledging the strong empirical base for CBT in anxiety disorders (Carpenter et al., 2018). Importantly, Kuyken et al. (2016) showed that MBCT prevents depressive relapse in clinical populations when delivered with fidelity, highlighting mechanisms such as decentering and altered cognitive reactivity that may plausibly contribute to lower anxiety as well—mechanisms consistent with the direction observed here, albeit within a simulated context. At the same time, Cuijpers et al. (2015) emphasised that psychological treatment effects often extend to broader functional domains; in real-world evaluations, such functional outcomes could complement symptom measures like the BAI and might modify classification performance or effect magnitudes. These links justify referencing MBCT's broader evidence base and potential functional benefits when interpreting patterns like those simulated here.

Nevertheless, our findings are illustrative rather than confirmatory. The data are fully simulated, restricted to post-treatment scores, and not intended for clinical generalisation; they show how complementary analyses would be reported if such differences emerged in applied research (Szuhany & Simon, 2022). Future didactic extensions could incorporate baseline covariates, repeated measures, or multilevel structures to contrast ANOVA with ANCOVA and mixed-effects modelling, and to examine robustness under assumption violations (Keselman et al., 2001; Field & Wilcox, 2017; Tabachnick & Fidell, 2001).

Limitations

First, all data are simulated; no participant recruitment, randomisation, or treatment delivery occurred. The means/SDs and truncation to the admissible BAI range (0–63) were specified a priori to yield a clinical-like, post-treatment distribution with realistic overlap. Second, the dataset includes post-treatment BAI only (BAI_Post); baseline and mid-treatment values were not simulated, precluding trajectory analyses or ANCOVA-style adjustment for initial severity. Third, sociodemographic variables were programmatically balanced with small, plausible imbalances; any apparent covariate effects are therefore illustrative, not empirical. Finally, performance metrics (AUC/accuracy) depend on the chosen thresholding strategy and the small sample size and should not be interpreted as benchmarks for clinical decision-making.

Conclusion

In a simulation-based, clinical-like example, one-way ANOVA + Cohen's d and binary logistic regression + AUC converged on the same substantive message—lower post-treatment anxiety in MBCT than CBT—while offering complementary interpretive angles: one centered on average differences, the other on discriminative utility. These perspectives are non-substitutable and should be reported and read together.

Because the dataset is fully synthetic and restricted to post-treatment outcomes, results are not intended for clinical generalisation; rather, they clarify how distinct inferential tools answer different questions about the same continuous endpoint and how their joint interpretation can strengthen didactic demonstrations in comparative effectiveness research. This study can be extended to ANCOVA or mixed-effects models when baseline or longitudinal data are available.

Supplementary Methods

Software Environment and Versions

To ensure full reproducibility, the analyses and figures were produced in the following environment: Python 3.12.4; NumPy 1.26.4; pandas 2.2.2; SciPy 1.13.1; stats models 0.14.2; scikit-learn 1.5.1; matplotlib 3.9.2.

Reproducible Artifact

A fully documented Python script (simulate_cbt_mbct_results.py) is provided; it recomputes all results and writes the compact figure (BAI_Post_by_group.png). Place the script and the CSV in the same directory and run: python simulate_cbt_mbct_results.py. It prints the tables to the console and saves the figure to disk.

References

1. Beck, A. T., Epstein, N., Brown, G., & Steer, R. A. (1988). An inventory for measuring clinical anxiety: Psychometric properties. *Journal of Consulting and Clinical Psychology, 56*(6), 893–897. https://doi.org/10.1037/0022-006X.56.6.893
2. Carpenter, J. K., Andrews, L. A., Witcraft, S. M., Powers, M. B., Smits, J. A. J., & Hofmann, S. G. (2018). Cognitive behavioral therapy for anxiety and related disorders: A meta-analysis of randomized placebo-controlled trials. *Depression and Anxiety, 35*(6), 502–514. https://doi.org/10.1002/da.22728
3. Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.
4. Committee on Publication Ethics (COPE) Council. (n.d.). *Studies requiring ethics approval*. https://publicationethics.org/guidance/cope-position/studies-requiring-ethics-approval
5. Cuijpers, P., Weitz, E., Karyotaki, E., Garber, J., & Andersson, G. (2015). The effects of psychological treatment of maternal depression on children and parental functioning: A meta-analysis. *European Child & Adolescent Psychiatry, 24*(2), 237–245. https://doi.org/10.1007/s00787-014-0660-6
6. Field, A. P., & Wilcox, R. R. (2017). Robust statistical methods: A primer for clinical psychology and experimental psychopathology researchers. *Behaviour Research and Therapy, 98*, 19–38. https://doi.org/10.1016/j.brat.2017.05.013
7. Hofmann, S. G., Sawyer, A. T., Witt, A. A., & Oh, D. (2010). The effect of mindfulness-based therapy on anxiety and depression: A meta-analytic review. *Journal of Consulting and Clinical Psychology, 78*(2), 169–183. https://doi.org/10.1037/a0018555
8. Hosmer, D. W., Jr., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression* (3rd ed.). John Wiley & Sons.
9. Keselman, H. J., Algina, J., & Kowalchuk, R. K. (2001). The analysis of repeated measures designs: A review. *British Journal of Mathematical and Statistical Psychology, 54*(1), 1–20. https://doi.org/10.1348/000711001159357
10. Khoury, B., Lecomte, T., Fortin, G., Masse, M., Therien, P., Bouchard, V., Chapleau, M.-A., Paquin, K., & Hofmann, S. G. (2013). Mindfulness-based therapy: A comprehensive meta-analysis. *Clinical Psychology Review, 33*(6), 763–771. https://doi.org/10.1016/j.cpr.2013.05.005

11. Kuyken, W., Warren, F. C., Taylor, R. S., Whalley, B., Crane, C., Bondolfi, G., Hayes, R., Huijbers, M., Ma, H., Schweizer, S., Segal, Z., Speckens, A., Teasdale, J. D., Van Heeringen, K., Williams, M., Byford, S., Byng, R., & Dalgleish, T. (2016). Efficacy of mindfulness-based cognitive therapy in prevention of depressive relapse: An individual patient data meta-analysis from randomized trials. *JAMA Psychiatry*, *73*(6), 565–574. https://doi.org/10.1001/jamapsychiatry.2016.0076
12. Li, J., Cai, Z., Li, X., Du, R., Shi, Z., Hua, Q., Zhang, M., Zhu, C., Zhang, L., & Zhan, X. (2021). Mindfulness-based therapy versus cognitive behavioral therapy for people with anxiety symptoms: A systematic review and meta-analysis of random controlled trials. *Annals of Palliative Medicine*, *10*(7), 7124–7136. https://doi.org/10.21037/apm-21-1212
13. Lix, L. M., & Keselman, H. J. (1996). Interaction contrasts in repeated measures designs. *British Journal of Mathematical and Statistical Psychology*, *49*(1), 147–162. https://doi.org/10.1111/j.2044-8317.1996.tb01079.x
14. Szuhany, K. L., & Simon, N. M. (2022). Anxiety disorders: A review. *JAMA, 328*(24), 2431–2445. https://doi.org/10.1001/jama.2022.22744
15. Tabachnick, B. G., & Fidell, L. S. (2001). *Computer-assisted research design and analysis*. Allyn and Bacon.

Acknowledgements
The authors gratefully acknowledge the use of open-source scientific computing libraries (NumPy, pandas, SciPy, statsmodels, scikit-learn, matplotlib) for data simulation and statistical analysis. No human participants were involved in this simulation-based methodological demonstration.

Funding
This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. No financial support was received for the design, collection, analysis, or reporting of this methodological study.

Conflict of Interest Statement
The authors declare no conflicts of interest related to this research.

Author Contributions (CRediT)
Wan-Chen Wang: Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Project administration.
Maria de Fátima Alves de Pina: Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Project administration.
Maria Helena de Aguiar Pereira e Pestana: Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Project administration.
Yu-Tso Liu: Data curation, Writing – review & editing.

Data and Code Availability Statement
The data and statistical code supporting the findings of this study are available from the corresponding author upon reasonable request.

Disclosure of Artificial Intelligence-Generated Content (AIGC) Tools
This manuscript was written by the authors without AI-generated content. The authors used DeepL and Gemini solely to check for grammatical errors and improve readability; all substantive content, analysis, and interpretation were produced by the authors. All statistical analyses were conducted using standard Python scientific computing libraries as documented in the Supplementary Methods.