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Optimizing Music Therapy for Depression Treatment: Investigating the Relationship Between Music Preferences and Mental Health

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ABSTRACT

Music therapy is a promising adjunct to depression care, yet effects likely vary with everyday listening. In a cross-sectional online survey (N = 736), we examined associations between preferred genres, self-reported typical tempo (beats per minute; BPM), and engagement mode (composing/playing/exploring vs. purely receptive) with single-item anxiety and depression (0–10). After prespecified cleaning (e.g., implausible BPM < 30 or > 300 excluded) and listwise analysis, we estimated OLS models with HC3 standard errors; genre differences used one-way ANOVA (inference restricted to adequately sized groups), reporting ω^2 and 95% CIs. Typical BPM showed small, positive linear associations with both anxiety and depression; the quadratic term was null and model R^2 values were modest. Genre effects were small at the omnibus level, and only a limited subset of pairwise contrasts remained significant after correction (e.g., Metal vs. Classical/R&B; Video-game music vs. Classical for anxiety). Active engagement showed selective, small associations (composition with lower depression) that warrant experimental tests. Findings, derived from a non-clinical, correlational dataset, argue for individualised use of music in practice and for prospective trials that manipulate engagement type and tempo within genres.

KEYWORDS

Music Therapy; Depression; Anxiety; Music Preferences; Beats Per Minute (BPM); Active Music Engagement; Mental Health

1. INTRODUCTION

1.1. Background

Depression and anxiety are prevalent worldwide and impose substantial personal and societal costs. Alongside standard treatments, interest has grown in music-based approaches because music can modulate affect, stress physiology, and reward processing in ways that may support symptom management (Aalbers et al., 2017; Erkkilä et al., 2011; Fancourt & Finn, 2019). Evidence syntheses suggest that music therapy can reduce depressive symptoms when added to usual care, yet effects vary by modality and context and are typically small-to-moderate (Aalbers et al., 2017; Fancourt & Finn, 2019).

At the neural and psychophysiological level, music engages cortico-subcortical systems central to emotion and reward and can shift autonomic and cardiorespiratory activity (Koelsch, 2014, 2020; Bernardi et al., 2006). Tempo is closely linked to arousal; slower, more stable rhythms are often associated with down-regulation and faster rhythms with heightened activation, consistent with dimensional models of affect and classic arousal–performance relations (Russell, 1980; Yerkes &

Dodson, 1908). These frameworks motivate examining whether typical listening tempo relates to anxiety and depression in everyday settings, while avoiding causal claims in observational data.

Beyond acoustic features, genre preferences and modes of engagement may matter. Stereotypes about "calming" or "agitating" genres are not uniformly supported; for example, extreme metal can facilitate adaptive anger processing among fans, highlighting the role of listener goals and context (Rentfrow & Gosling, 2003; Sharman & Dingle, 2015). Meanwhile, active participation (e.g., playing or composing) is often argued to foster mastery, agency, and social connection, aligning with contemporary frameworks that link music engagement to well-being, though effects are heterogeneous and context-dependent (Gustavson et al., 2021; Fancourt & Finn, 2019).

1.2. Aim

This study addresses these gaps by examining associations (not causal effects) between everyday music behaviours and self-reported symptoms in a community sample (N = 736). We ask: (Q1) Is higher typical listening tempo associated with greater anxiety and depression symptoms, as predicted by arousal-based models? (Q2) Do favourite-genre preferences show small but reliable differences in symptom levels, acknowledging potential stereotype mismatches? (Q3) Is active engagement (especially composing/creating) associated with lower symptoms than purely receptive listening, consistent with contemporary accounts of music-supported well-being (Gustavson et al., 2021)? These questions are intended to prioritise which everyday characteristics warrant targeted testing in subsequent controlled interventions (Aalbers et al., 2017; Fancourt & Finn, 2019).

2. METHODOLOGY

We analysed de-identified responses from a publicly available, non-clinical community survey (N = 736) that captured demographics, everyday music behaviours, and symptom ratings. The dataset was accessed in anonymised form; geographic and cultural identifiers were not retained, so generalisability is considered cautiously in the Discussion. This project constituted observational secondary analysis of existing data.

2.1. Participants and Data Source

All respondents provided self-reports via an online questionnaire. No intervention or clinical procedures were involved. A data-flow diagram summarises inclusion and model-specific analytic Ns (listwise deletion; no imputation).

2.2. Measures

Anxiety and depression were each assessed with single-item 0–10 numeric ratings (higher scores = greater symptoms). These brief indicators are suitable for population surveys but do not substitute for diagnostic instruments; all inferences are associational.

2.3. Music-related Predictors and Coding

Typical listening tempo was a self-reported beats-per-minute (BPM) estimate reflecting the music participants usually listen to (not audio-extracted). For modelling, BPM was mean-centred (BPM_c), and a quadratic term (BPM_c^2) probed potential non-linearity suggested by arousal frameworks.

Genre preference was derived from 0–3 frequency ratings across multiple genres: each genre's raw score was normalised by the respondent's total to yield proportional weights, and the primary (favourite) genre was the category with the highest weight (ties resolved by higher raw value, then alphabetically). To capture shared variance in taste, a principal components analysis on genre-frequency items produced a first component score (GenrePC1), used as a covariate.

Modes of engagement were coded from binary items: instrumentalist (0/1), composer (0/1), and exploratory listening (seeks new artists/genres; 0/1). An “active” indicator equalled 1 if instrumentalist = 1 or composer = 1; otherwise 0. A single item recorded whether “music helps” mood (0/1) and was used descriptively and as a covariate.

2.4. Analytic Strategy

Associations between tempo and each symptom were estimated with ordinary least squares (OLS) models including BPM_c and BPM_c² and adjusting for age, daily listening hours, exploratory listening, instrumentalist, composer, “music helps,” and GenrePC1. Inference used heteroskedasticity-consistent Heteroskedasticity-Consistent (HC3) standard errors with two-sided tests and 95% confidence intervals (Hayes & Cai, 2007).

Genre differences were examined with one-way Analysis of Variance (ANOVA), retaining primary-genre groups with $n \geq 30$ for inference; under the present data this yielded $k = 10$ groups (df_between = 9; df_within = 726). When the omnibus test was significant, pairwise contrasts used Tukey’s procedure, and false discovery rate control (Benjamini & Hochberg, 1995; Tukey, 1949) was applied as a sensitivity check.

Active versus passive comparisons used Welch’s unequal-variance t-tests with Hedges-adjusted Cohen’s d and 95% CIs as the effect-size metric (Welch, 1947; Cohen, 1988).
Model diagnostics (residual plots, influence, variance-inflation factors) followed prespecified thresholds. Algebraic details and additional robustness checks are reported in Appendix A; numeric estimates are presented only in the Results.

2.5. Missing data and analytic samples

Analyses proceeded listwise without imputation. Because covariate availability varied across respondents, analytic Ns differed by model; model-specific Ns are reported alongside results and visualised in the data-flow figure.

Hypotheses

H1 (Tempo–anxiety). Consistent with arousal frameworks, higher typical listening BPM would be positively associated with anxiety (small effect expected) after adjusting for demographics and listening-habit covariates.

H2 (Tempo–depression). Higher BPM would be positively associated with depression (small effect expected). A quadratic term was explored without directional assumptions.

H3 (Genre differences). Mean anxiety and depression would differ modestly across primary-genre groups, acknowledging that genre effects are likely heterogeneous and context-dependent.

H4 (Active engagement). Active engagement (particularly composing) would be associated with lower symptoms than purely receptive listening, consistent with agency/self-efficacy accounts; effects were expected to be small.

3. RESULTS

This section summarises the empirical findings from three complementary analyses: associations between typical listening tempo and symptoms, differences across favourite-genre groups, and contrasts between active versus purely receptive engagement. Full coefficient tables and diagnostic summaries accompany each analysis.

3.1. Tempo Analysis: Hierarchical Regression of BPM on Anxiety and Depression

Beats-per-minute (BPM)—the pace of one's typical listening—has long been linked to physiological arousal and affective tone. This subsection examines whether BPM is associated with self-reported anxiety and depression after accounting for demographic and listening-habit covariates, and whether any non-linear pattern emerges within the observed tempo range

3.1.1. Data & Variables

To keep the analysis reproducible and compact, the study used harmonised variable definitions and deterministic coding. Table 3-1 summarises outcomes, predictors, and covariates.

Table 3-1. Variables and coding

Variable	Type	Coding / Construction	Notes
Anxiety	Outcome	Single-item 0–10 self-rating	Higher = more anxious
Depression	Outcome	Single-item 0–10 self-rating	Higher = more depressed
BPM_c	Focal predictor	Self-reported typical BPM, mean-centered	Continuous
BPM_c²	Focal predictor	Square of BPM_c	Tests curvature (non-linearity)
Age	Covariate	Years (self-report)	Continuous
Hours per day	Covariate	Usual daily listening hours	Continuous
Exploratory	Covariate	0 = No, 1 = Yes	Seeks new artists/genres
Instrumentalist	Covariate	0 = No, 1 = Yes	Plays an instrument
Composer	Covariate	0 = No, 1 = Yes	Writes/creates music
Music helps	Covariate	0 = No, 1 = Yes	Perceived mood benefit of music
GenrePC1	Covariate	First PC from 12 genre-frequency items	Signs oriented for interpretability; full loadings in Table S1

3.1.2. Statistical Model

Associations between tempo and each symptom were estimated via linear models including BPM_c and BPM_c², adjusted for the covariates listed above. Inference used HC3 heteroskedasticity-consistent standard errors; two-sided tests with 95% CIs; model fit summarised with R^2 / adjusted R^2. Table 3-2 provides a one-page specification summary.

Table 3-2. Model specification summary

Item	Anxiety model	Depression model
Outcome	Anxiety (0–10)	Depression (0–10)
Core terms	BPM_c, BPM_c²	BPM_c, BPM_c²
Covariates	Age; Hours per day; Exploratory; Instrumentalist; Composer; Music helps; GenrePC1	Age; Hours per day; Exploratory; Instrumentalist; Composer; Music helps; GenrePC1
SEs / Tests	HC3 robust SE; two-sided tests; 95% CIs	HC3 robust SE; two-sided tests; 95% CIs
Fit indices reported	R^2, adjusted R^2	R^2, adjusted R^2
Diagnostics	Residuals, VIF, influence, False Discovery Rate (FDR) sensitivity	Residuals, VIF, influence, FDR sensitivity

3.1.3. Results

Typical listening tempo showed small, positive associations with both symptoms after adjustment; the quadratic term was not significant, indicating no reliable curvature across the observed tempo range (see Tables 3-3).

For anxiety, BPM_c: $b = 0.0116$, 95% CI [0.0082, 0.0149], $p < .001$; model $R^2 = 0.079$ (adjusted 0.068). BPM_c² n.s. ($p = .543$).

For depression, BPM_c: $b = 0.0088$, 95% CI [0.0055, 0.0121], $p < .001$; model $R^2 = 0.064$ (adjusted 0.053). BPM_c² n.s. ($p = .539$).

Among covariates, Composer = 1 related to lower depression ($b = -0.244$, 95% CI [−0.426, −0.062], $p = .0087$). Reporting that music helps related to lower anxiety ($b = -0.195$, 95% CI [−0.385, −0.005], $p = .044$) and lower depression ($b = -0.337$, 95% CI [−0.524, −0.149], $p < .001$). Exploratory was associated with slightly lower anxiety ($b = -0.179$, 95% CI [−0.341, −0.017], $p = .030$). Other covariates were small or unstable.

Table 3-3. Linear regression of Anxiety on tempo and covariates

Predictor	b	95% CI lower	95% CI upper	p
Intercept	4.888	4.424	5.353	<.001
BPM_c	0.0116	0.0082	0.0149	<.001
BPM_c²	0	-0.0001	0.0001	.543
Age	0.0032	-0.012	0.0185	.678
Hours per day	0.0262	-0.027	0.0793	.334
Exploratory (1)	-0.1786	-0.3406	-0.0166	.030
Instrumentalist (1)	0.0978	-0.0699	0.2655	.253
Composer (1)	-0.1562	-0.3305	0.018	.079
Music helps (1)	-0.1949	-0.3844	-0.0055	.044
GenrePC1	0.0026	-0.0721	0.0772	.947

Typical listening tempo is positively associated with anxiety after adjustment, but the magnitude is small (roughly +0.12 points per +10 BPM on a 0–10 scale). The quadratic term is null, so there is no evidence of curvature within the observed range. Two covariates show small protective patterns—Exploratory listening and endorsing that music helps—while other predictors are near zero. Overall, tempo adds incremental explanatory value rather than being a decisive predictor.

Table 3-4. Linear regression of Depression on tempo and covariates (HC3)

Predictor	b	95% CI lower	95% CI upper	p
Intercept	5.1845	4.7458	5.6231	<.001
BPM_c	0.0088	0.0055	0.0121	<.001
BPM_c²	0	-0.0001	0.0001	.539
Age	0.0052	-0.0094	0.0199	.483
Hours per day	-0.0423	-0.0894	0.0048	.079
Exploratory (1)	-0.0964	-0.2561	0.0634	.237
Instrumentalist (1)	-0.1012	-0.2649	0.0626	.226
Composer (1)	-0.2439	-0.4261	-0.0617	.0087
Music helps (1)	-0.3367	-0.5239	-0.1495	<.001
GenrePC1	0.0372	-0.0354	0.1098	.316

Higher typical BPM is also modestly associated with higher depression, again linear, not curvilinear. The standout covariate is Composer = 1, which relates to lower depression, consistent with benefits that often co-occur with creative engagement (interpretation is correlational). Reporting that music helps likewise aligns with lower depression, whereas GenrePC1 is non-significant, suggesting the tempo–depression link is not simply a proxy for a broad "high-energy taste" axis.

3.2. Genre Differences In Symptoms and Perceived Helpfulness

This subsection reports genre-related differences in self-reported anxiety and depression, as well as perceived helpfulness of music. Variable construction and cleaning appear in Section 2; here we focus on descriptive summaries, omnibus tests, and corrected pairwise contrasts. All effects are interpreted as associations and are generally small.

3.2.1. Methodology

Table 3-5 summarises primary-genre groups (N per group, mean ± SD for anxiety and depression, and the percentage reporting that music helps). Differences at the descriptive level are modest overall. Genres often labelled as "calmer" (e.g., Classical, R&B) show lower average symptoms alongside relatively high perceived helpfulness, whereas Rock and Metal tend higher. Small-N genres (e.g., Gospel, Lofi, Latin) are retained for completeness but are descriptive only and not used for inference (flagged below).

Table 3-5. Mental-health outcomes by primary music genre

Genre	N	Anxiety (M ± SD)	Depression (M ± SD)	% Music helps
Classical	53	4.9 ± 2.9	4.1 ± 3.1	72%
Country	25	5.4 ± 3.0	4.3 ± 3.2	80%
EDM	37	5.5 ± 3.4	5.2 ± 3.1	83%
Folk	30	6.6 ± 2.6	5.1 ± 2.9	79%
Gospel	6	4.8 ± 3.2	2.7 ± 3.9	100%
Hip hop	35	6.2 ± 2.4	5.8 ± 2.7	89%
Jazz	20	5.9 ± 2.8	4.5 ± 3.2	80%
K-pop	26	6.2 ± 2.6	4.4 ± 3.1	83%
Latin	3	4.3 ± 5.1	3.0 ± 3.0	50%
Lofi	10	6.1 ± 2.1	6.6 ± 3.1	100%
Metal	88	5.8 ± 3.0	5.1 ± 3.0	76%
Pop	114	6.1 ± 2.4	4.5 ± 2.6	71%
R&B	35	5.2 ± 2.8	3.8 ± 3.1	74%
Rap	22	5.1 ± 2.9	4.0 ± 3.1	73%
Rock	188	6.1 ± 2.9	5.2 ± 3.1	64%
Video game music	44	5.9 ± 2.5	4.5 ± 2.8	50%

Group differences are small overall. Classical and R&B show lower average symptoms with higher perceived helpfulness; Rock and Metal trend higher. Extremely high or low percentages in small-N genres (e.g., Gospel = 100%, Lofi = 100%) should be treated as anecdotal rather than inferential.

3.2.2. Omnibus tests

One-way ANOVAs indicated small between-genre dispersion among $n \geq 30$ groups ($k = 10$; $F(9, 726)$ = …) (Table 3-6); small-N genres were not included in inference.

Table 3-6. One-way ANOVA Results for Anxiety and Depression Across Primary Music Genres

Outcome	df_between	df_within	F	p	eta2	omega2
Anxiety	9	726	3.77	0.00012	0.045	0.033
Depression	9	726	2.7	0.0043	0.032	0.02

3.2.3. ANOVA Significance Testing:

Building on the omnibus ANOVAs, we conducted Tukey's Honestly Significant Difference test (Tukey HSD) comparisons among the primary-genre groups retained for inference (groups with adequate sample sizes; see Table 3-7). After controlling the familywise error rate, only a limited subset of contrasts remained reliable, underscoring that between-genre differences are detectable but small. For depression, listeners who primarily endorsed Metal reported higher average scores than those preferring Classical ($\Delta M = 0.715$, 95% CI [0.113, 1.316], $p = .0067$) and R&B ($\Delta M = 0.584$, 95% CI [0.006, 1.161], $p = .045$). On the 0–10 outcome scale, these deltas correspond to ~0.6–0.7 points—statistically reliable yet modest in magnitude—consistent with the small omnibus effect sizes ($\omega^2 \approx 0.02$). No other depression contrasts survived correction, indicating that most genre pairs are indistinguishable once multiplicity is accounted for.

Table 3-7. Tukey HSD Post-hoc Pairwise Comparisons of Anxiety and Depression Across Primary Music Genres

Outcome	Group1	Group2	Mean diff	Lower CI	Upper CI	p_adj
Depression	Metal	Classical	0.715	0.113	1.316	0.0067
Depression	Metal	R&B	0.584	0.006	1.161	0.045
Anxiety	Metal	Classical	0.705	0.095	1.316	0.0098
Anxiety	Video game music	Classical	0.632	0.06	1.204	0.0172
Anxiety	Metal	R&B	0.613	0.027	1.199	0.032

For anxiety, a similar pattern emerged: Metal exceeded Classical ($\Delta M = 0.705$, 95% CI [0.095, 1.316], $p = .0098$) and R&B ($\Delta M = 0.613$, 95% CI [0.027, 1.199], $p = .032$), and Video-game music exceeded Classical ($\Delta M = 0.632$, 95% CI [0.060, 1.204], $p = .0172$). Again, the absolute differences are small (≈0.6–0.7 on a 0–10 scale), and the direction aligns with the descriptive means (Table 3-5) in which calmer or more melodic genres tended to sit lower. All other anxiety contrasts did not remain significant after correction, highlighting substantial within-genre heterogeneity and reminding us that genre labels capture broad tendencies rather than homogeneous listener profiles.

Taken together, these corrected contrasts sharpen (but do not overturn) the omnibus findings: a few consistent pairings—particularly comparisons involving Metal versus Classical/R&B, and Video-game music versus Classical—show small elevations in symptoms. As a sensitivity check, the same set of pairwise conclusions held under an FDR control, reinforcing that the pattern is not an artifact of a single multiplicity procedure. Given uneven group sizes and the exclusion of small-N categories from inference, these differences should be interpreted as associations of limited practical magnitude rather than prescriptive guidance. Visual summaries of the significant contrasts with 95% CIs are provided in Figure 3-2, and full Tukey outputs appear in Table 3-7.

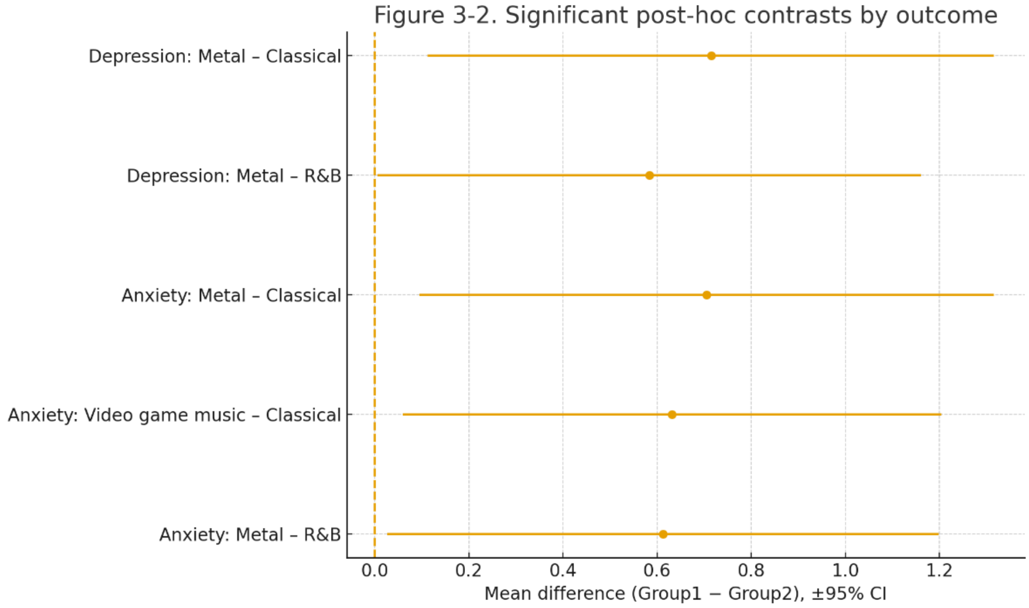

Figure 3-2. Significant post-hoc contrasts by outcome

3.2.4. Reverse-lookup

To complement the genre-to-symptom analyses, we report a reverse-lookup that transposes the contingency structure: for each integer value on the single-item 0–10 depression scale, we tabulate the number of listeners whose primary genre falls in each category (full counts in Table 3-8). Because raw counts are strongly influenced by base rates (e.g., Rock is the largest group overall), interpretation prioritises column-normalised shares—the proportion of each depression score band accounted for by each genre—summarised visually in Figure 3-3. This display is descriptive and exploratory; no inferential testing was planned for this subsection.

Table 3-8. Distribution of Primary Music Genres Across Depression Score Levels (0–10)

Genre	0	1	2	3	4	5	6	7	8	9	10
Rock	13	25	37	11	10	11	24	29	17	12	20
Classical	10	7	9	4	1	5	7	6	6	3	0
Metal	9	6	9	11	8	3	14	10	13	7	3
Pop	7	19	27	8	11	14	15	14	10	4	2
R&B	6	5	6	2	4	2	5	3	1	0	3
Video game music	4	8	8	5	4	5	7	3	4	0	3
EDM	3	4	5	2	5	2	3	6	4	3	3
Jazz	3	5	5	1	2	0	1	3	4	0	1
Rap	3	3	4	4	0	3	2	1	2	1	1
Gospel	2	1	1	0	1	0	0	0	0	0	1
K-pop	2	4	4	3	3	1	1	3	3	2	1
Folk	3	1	3	2	5	3	2	7	1	2	2
Hip hop	2	2	3	3	3	1	4	10	5	2	2
Country	3	2	7	2	1	5	1	1	3	2	1
Latin	1	0	1	1	0	0	1	0	0	0	0

At the lower end of the distribution (scores 0–2), the landscape is dominated by Rock in absolute terms, which mirrors its high overall prevalence in the sample. After column normalisation, Classical appears relatively more represented than at higher symptom levels, while Pop gains a noticeable presence by score 2, consistent with the notion that a substantial segment of asymptomatic or minimally symptomatic listeners favour mainstream contemporary styles. Genres often associated with higher physiological arousal (e.g., Metal, Hip hop, EDM) are observable in these columns but typically constitute <15% of each band, indicating that they are not absent at low scores but are comparatively less prominent.

Across the mid-range (scores 3–6), Rock continues to contribute the largest share, again reflecting its base rate; however, Metal becomes more prevalent relative to Classical from approximately score 3 onward. Pop maintains a stable share and peaks around score 5 before tapering. Importantly, Hip hop and Video-game music begin to show discernible upticks by score 6. This mid-range pattern is consistent with the earlier ANOVA results and pairwise contrasts (Section 3.2.3), which indicated small elevations for Metal and Video-game music on at least one outcome, albeit with substantial within-genre variability.

At the upper end (scores 7–10), the share of Rock and Metal increases further, while Classical/Jazz/Gospel become sparse in absolute counts. Hip hop exhibits a clearer presence at score 7, and EDM appears intermittently across scores 8–10. These patterns align qualitatively with the descriptive means (Table 3-5) and the corrected pairwise contrasts, but they should be interpreted cautiously: the display aggregates across listeners with heterogeneous motives and contexts, and genre labels necessarily capture broad stylistic families rather than psychometrically uniform categories.

Two considerations temper the interpretation. First, small-N genres (e.g., Gospel, Latin, Lofi) generate unstable cells in several score bands; these entries are retained for completeness but are flagged as descriptive only. Second, even for large-N genres, base-rate asymmetries mean that absolute counts can overstate prominence within a score band; hence our emphasis on column percentages and the heat-map representation. As a sensitivity check, re-expressing the table as row-normalised shares (genre distributions across scores) and as a mosaic plot does not alter the qualitative direction of the patterns, though it further highlights the heterogeneity within genres.

This reverse-lookup is intended to be hypothesis-generating, not prescriptive. It may inform subsequent, pre-registered tests that model the probability of endorsing a given primary genre as a function of depression level while adjusting for covariates (e.g., age, hours/day, exploratory listening, musician status). Likewise, future studies could examine whether the observed increases in the relative share of Metal and Video-game music at higher scores replicate in more diverse samples, and whether they persist when genre engagement is operationalised via objective listening logs rather than self-report. In the present cross-sectional data, however, the patterns are best read as small-magnitude associations that echo—without strengthening—the genre differences reported in Sections 3.2.1–3.2.3.

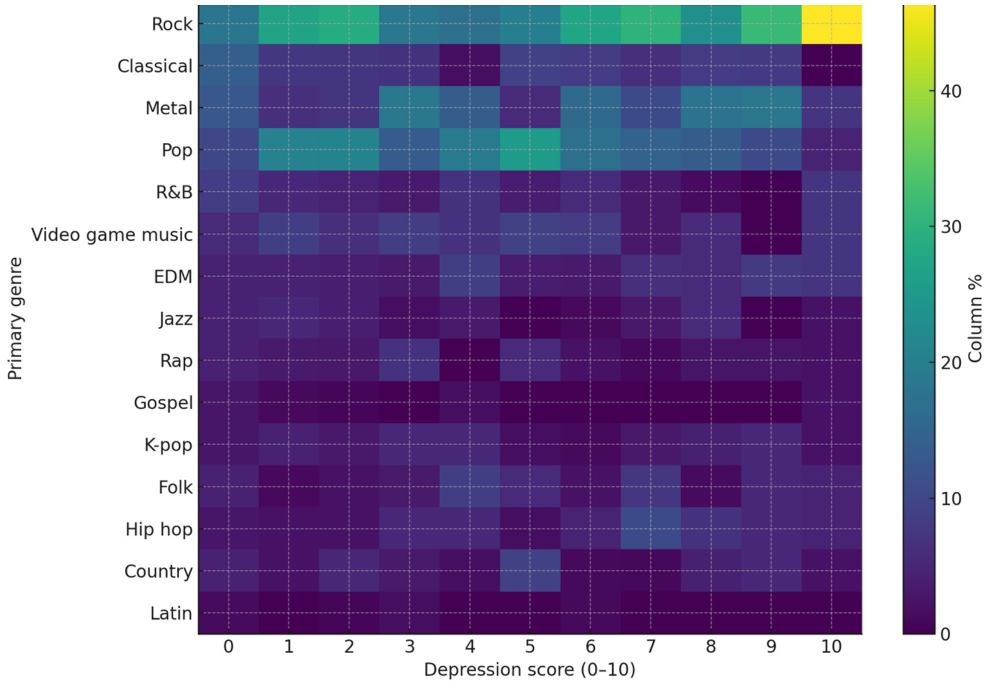

Figure 3-3. Column-normalised Distribution of Music Genres Across Depression Levels

4. DISCUSSION

This study examined three facets of everyday music use—typical tempo, primary-genre preference, and mode of engagement—in relation to self-reported anxiety and depression. Across analyses, effects were statistically detectable yet small, and inferences are associational given the cross-sectional, self-report design.

The tempo findings suggest a modest, linear relation with symptoms. In adjusted models, higher typical BPM was associated with slightly higher anxiety ($b = 0.0116$, 95% CI [0.0082, 0.0149]) and depression ($b = 0.0088$, [0.0055, 0.0121]); the quadratic term was null, indicating no reliable curvature across the observed range. On a 0–10 scale, a 10-BPM increase corresponds to ≈ +0.12 anxiety points and ≈ +0.09 depression points. Explained variance remained modest ($R^2 = 0.079$ and 0.064), underscoring that tempo by itself is a limited indicator of mood in naturalistic listening. These data therefore do not support recommending simple tempo thresholds (e.g., "< 100 BPM") as a rule of thumb; a more defensible approach is individualised selection of tracks perceived as calming, with symptom-contingent monitoring rather than BPM-based prescriptions. This interpretation is consistent with broader evidence that clinically delivered music therapy can benefit mood, while specific musical parameters (such as tempo alone) are rarely sufficient without therapeutic framing and engagement structure. (Aalbers et al., 2017; Erkkilä et al., 2011; Tang et al., 2020).

Genre analyses revealed small between-group differences. Omnibus tests showed significant but small dispersion ($\omega^2 \approx 0.02$–0.03), and only a limited subset of pairwise contrasts survived multiple-comparison correction (e.g., Metal > Classical/R&B; Video-game music > Classical for anxiety). Effect magnitudes were ≈ 0.6–0.7 points on a 0–10 scale—detectable, but not large. Descriptively, groups often labelled "calmer" (Classical, R&B) tended to report lower averages, whereas Rock/Metal were higher; however, many contrasts were not reliable after correction and within-genre heterogeneity was substantial. Small-N genres (e.g., Gospel, Lofi, Latin) produced extreme percentages that should be treated as descriptive rather than inferential. Collectively, genre appears most useful as contextual information for personalisation, not as a prescriptive rule about what patients "should" or "should not" hear.

Engagement quality showed selective associations. Reporting composition was associated with lower depression (Table 3-4), converging with theoretical accounts that creative, self-directed musical activity can co-occur with mastery, agency, and reward processes—factors frequently emphasised in therapeutic music making. At the same time, instrumentalist status was not consistently protective, and daily listening hours showed at most trend-level relations, indicating that what people do with music may matter more than simply being "active." Because observational data cannot exclude reverse causation or self-selection (e.g., individuals with lower symptoms may be more likely to compose), experimental tests are needed to evaluate whether composition-focused interventions yield incremental benefit beyond receptive listening or instrumental practice. Recent reviews echo this direction by highlighting stronger effects when interventions include active, therapist-guided components rather than unguided listening alone. (Aalbers et al., 2017; de Witte et al., 2020/2022).

Several limitations qualify interpretation. First, the survey is non-clinical and cross-sectional with self-reported single-item symptom ratings; clinical scales (e.g., PHQ-9/GAD-7) were not administered here, and reliability could not be estimated. Second, genre preference and "music helps" are self-perceptions and may be influenced by expectancy or demand characteristics. Third, small group sizes for some genres limit precision and generalisability; we therefore excluded $N < 20$ genres from inferential tests and flagged them as descriptive. Fourth, cultural and regional context was not modelled, despite known cultural patterning of music taste. Finally, unmeasured confounds (e.g., socioeconomic status, formal training, comorbidity, treatment status) may partially account for observed associations. These caveats argue for cautious interpretation and for follow-up work that directly addresses them.

Looking forward, the present results generate testable hypotheses rather than prescriptive rules. Two directions appear especially actionable: (a) composition-focused RCTs (vs. receptive listening and vs. instrumental practice) with pre-registered outcomes, adequate power, and clinician-rated measures; and (b) within-genre tempo manipulations to isolate arousal effects without conflating tempo and style, ideally using objective listening logs and ambulatory mood sampling. Such designs would clarify mechanisms noted in prior trials and meta-analyses while improving translational relevance to clinical music therapy. (Aalbers et al., 2017; Erkkilä et al., 2011; Tang et al., 2020).

5. CONCLUSION

Personalisation along three axes—tempo, genre context, and engagement quality—may improve how music is used to support mood management, but decisions should be client-centred, data-informed, and non-prescriptive. In this dataset, (i) typical tempo shows a small, linear association with symptoms and offers no evidence for simple tempo thresholds; (ii) genre differences are small with only a few reliable contrasts after correction, suggesting genre should guide starting points rather than rules; and (iii) creative engagement (composition) is associated with lower depression and warrants experimental evaluation. Clinicians might therefore prioritise collaborative selection of music the client experiences as soothing, consider structured opportunities for songwriting or guided creation, and track outcomes over time—choices that are consistent with the broader clinical literature on music therapy while remaining faithful to the associational nature of the present findings. (Aalbers et al., 2017; Erkkilä et al., 2011; Tang et al., 2020; de Witte et al., 2020/2022).

6. LIMITATIONS

All variables—listening habits, primary-genre, engagement, and symptoms—were self-reported, which introduces recall and desirability biases; the single-item 0–10 symptom ratings preclude reliability estimates and likely attenuate associations. The sample is non-clinical and cross-sectional, so findings are associational and not evidence of therapeutic efficacy of any specific tempo, genre, or engagement mode. Group sizes were uneven across genres; several categories had small N and were treated as descriptive only. Even among larger groups, base-rate asymmetries can inflate raw counts in the reverse-lookup display, hence our emphasis on column-normalised percentages and multiplicity-corrected contrasts; effect sizes remained small overall. Listwise deletion yielded different analytic Ns and may introduce selection bias relative to imputation approaches.

Operationalisation of tempo relied on self-reported top tracks, which may not capture situational listening or within-genre variability; measurement error would bias BPM slopes toward zero, whereas unmeasured confounds (e.g., treatment status, training, SES, sleep) could distort estimates in either direction. Genre labels are broad cultural categories; absent modelling of cultural/linguistic context limits generalisability.

Future work should use pre-registered randomised designs that compare composition vs. receptive listening vs. instrumental practice and manipulate tempo within genres; include validated multi-item scales (e.g., PHQ-9/GAD-7) and ambulatory mood sampling; incorporate objective listening logs with audio-derived tempo and non-linear modelling; recruit larger, more diverse samples with planned subgroup tests, and address missingness and clustering via multiple imputation and multilevel models.

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