The Effectiveness of Fast- vs. Slow-Tempo Music on Students' Cognitive Performance: A Within-Subject Experimental Design

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ABSTRACT

This study examined the effects of music tempo on students' cognitive performance under three conditions: fast-tempo, slow-tempo, and no-music. Despite widespread use of music during studying, it remains empirically unclear whether and how music tempo differentially affects cognitive performance among junior high school students in Indonesia. A quantitative approach with a within-subject repeated measures experimental design was employed, involving 34 ninth-grade students from a junior high school in Indonesia. Each participant completed mathematical problem-solving tasks under three controlled conditions: fast-tempo instrumental music (120–190 BPM), slow-tempo instrumental music (60–80 BPM), and silence. Cognitive performance was measured using accuracy scores and subjective cognitive load assessed through the NASA-TLX. Data were analyzed using Repeated Measures ANOVA and validated with the Friedman test due to partial violations of normality assumptions. The results indicated that the fast-tempo condition produced the highest mean accuracy ($M = 73.53$), followed by no music ($M = 67.65$) and slow-tempo music ($M = 66.76$). However, the differences were not statistically significant, $F(2,\ 66)\ =\ 2.659,\ p\ =\ .078$, although a moderate effect size ($\eta^2 g = .052$) suggested practical relevance. Pairwise comparisons revealed a consistent trend favoring fast-tempo music over slow-tempo and no-music conditions. Notably, NASA-TLX scores indicated that the fast-tempo condition produced significantly lower perceived cognitive load (M = 50.07) compared to slow-tempo (M = 61.59), $\chi^2(2) = 13.41$, p = .001, suggesting that fast-tempo music reduced subjective mental effort even when accuracy gains were not statistically significant. These findings support the theoretical perspectives of Cognitive Load Theory and arousal-mood theory, indicating that optimal levels of auditory stimulation may enhance cognitive processing efficiency. The results highlight the practical relevance of fast-tempo music in academic settings and underscore the need for further research with larger samples and physiological measures.

Keywords: Music tempo, cognitive performance, repeated measures design, cognitive load, arousal-mood theory

1. INTRODUCTION

The use of music as a supportive stimulus in academic activities has become a common practice among students. Around 62–78% of students report the habit of listening to music while studying or doing tasks (Wei et al., 2025). This phenomenon has developed alongside increased access to music streaming platforms and the belief that music can enhance concentration and reduce academic stress (Khan et al., 2026). However, empirical evidence shows that the effectiveness of music on cognitive performance is highly dependent on the characteristics of the music (Gupta, 2025). Lin et al. (2023) found that slow-tempo music (60–80 BPM) actually decreases cognitive processing speed and task accuracy by 12% compared to conditions without music, while fast-tempo music shows varied results. These findings indicate that music cannot be treated as a universal stimulus that always has a positive impact, but rather requires a deep understanding of how tempo and music characteristics interact with students' cognitive processes (Moreno & Woodruff, 2024).

Although various studies have examined the effects of music on academic performance, most studies emphasize the aspect of personalization and individual preferences without systematically controlling for objective music characteristics. Milman & Paz-Baruch (2025) found that self-selected music significantly improves the mathematics performance of adolescents, while research on the role of mood and arousal shows that music can enhance reaction speed through mediation by positive mood and optimal levels of alertness (Kiss & Linnell, 2024). Other studies highlight that the cognitive load induced by external auditory stimuli is addictive to the intrinsic cognitive load of the task itself, so music with a certain level of complexity has the potential to worsen performance on tasks requiring significant cognitive resources (Evans et al., 2024). On the other hand, Hofbauer et al. (2024) research shows that music tempo significantly interacts with task characteristics: on tasks requiring serial processing, fast-paced music actually improves accuracy by synchronizing cognitive rhythm with auditory stimuli.

Research studies generally do not compare the effects of different musical tempos within a single experimental design with strict control over individual variables, particularly in the population of junior high school students who have different cognitive developmental characteristics and academic loads than college students or adults. This gap creates significant practical problems: teachers and students in grade IX facing the National Examination or Competency Assessment do not have evidence-based guidance on the type of music that is effective or may hinder their cognitive performance (Wei et al., 2025). Thus, a clear empirical gap exists: no study to date has directly compared the effects of fast-tempo, slow-tempo, and no-music conditions on the cognitive performance of Indonesian junior high school students within a single controlled within-subject design.To address this gap, this study employs a within-subject experimental design that compares the cognitive performance of ninth-grade (class IX) students across three music conditions: fast tempo (120–190 BPM, electronic instrumental), slow tempo (60–80 BPM, ambient instrumental), and no music. The within-subject approach was chosen to control for individual variability in music preferences and initial cognitive abilities (Arboleda et al., 2022). By integrating the Cognitive Load Theory perspective, which explains how external stimuli affect cognitive load within limited working memory (Evans et al., 2024), as well as the arousal-mood theory that emphasizes the role of optimal alertness in cognitive performance (Kiss & Linnell, 2024), this study aims to contribute new empirical evidence to the literature on the effects of music tempo in the context of Indonesian secondary education.

Specifically, this study aims to: (1) analyze the cognitive performance differences of class IX students under fast-tempo music, slow-tempo music, and no music conditions; (2) identify the optimal music conditions to support complex cognitive tasks as measured by response accuracy and subjective cognitive load (NASA-TLX); and (3) test the applicability of Cognitive Load Theory and arousal-mood theory in the context of music use among junior high school students in Indonesia. Practically, the results of this study are expected to provide evidence-based recommendations for educators and students in selecting appropriate supportive music for academic activities, as well as serve as a basis for developing more effective learning strategies in junior high school education.

2. RESEARCH METHOD

2.1. REASERCH DESIGN

This study employs a quantitative approach with a repeated measures experimental design (within-subject design), where each participant experiences all three treatment conditions: fast-paced music, slow-paced music, and no music. The within-subject design was chosen to control for individual variability in initial cognitive ability and music preference, allowing for the isolation of the pure effect of music conditions more validly (Vincenzi et al., 2022). The study implements counterbalancing using a Latin Square design with six different treatment sequences (ABC, ACB, BAC, BCA, CAB, CBA), with participants randomly distributed using a random number generator. Each condition is separated by a minimum 10-minute rest interval to minimize fatigue effects.

The three treatment conditions are: (1) fast-tempo music, which is electronic instrumental music with a tempo of 120–190 BPM without vocals, taken from a Spotify playlist; (2) slow-tempo music, which is ambient instrumental music with a tempo of 60–80 BPM without vocals; and (3) no music as a control condition. The choice of tempo ranges refers to the study by Lin et al. (2023), which found that music with a tempo of 60–80 BPM reduces cognitive processing speed, while tempos of 120–190 BPM show varied effects.

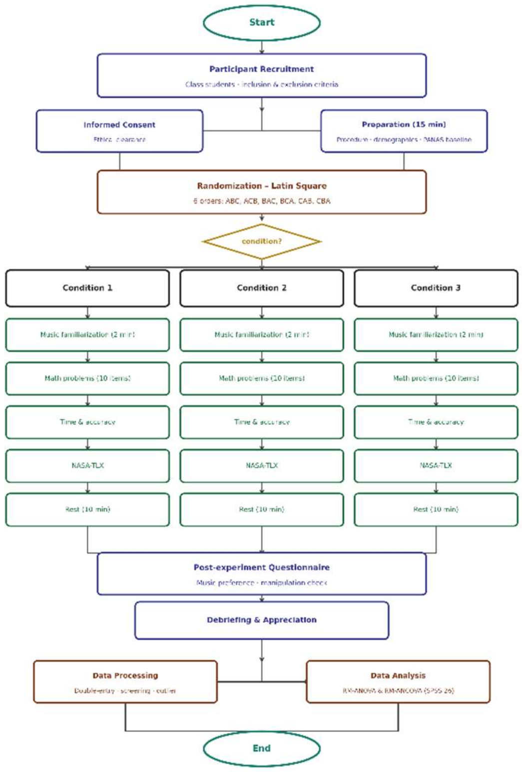

Figure 1. research flowchart

2.2. PARTICIPANTS

This research was conducted in one of the junior high schools in Purwakarta using purposive sampling technique. The inclusion criteria included: (1) being actively enrolled as a class IX student for the 2025/2026 academic year; (2) not having diagnosed hearing impairments or learning disabilities; (3) willing to participate voluntarily; and (4) present for all experimental sessions. The exclusion criteria included students who were currently taking medication affecting concentration or were sick on the day of the experiment.

Based on power analysis using G*Power 3.1 with the assumption of a medium effect size ($f = 0.25$), significance level $\alpha = 0.05$, power = 0.80, and three repeated measures, the minimum sample size required is 28 participants (Vincenzi et al., 2022). This study involved 34 students, thus exceeding the minimum required threshold. All participants have signed the informed consent form after receiving a complete explanation of the research objectives, procedures, minimal risks, data confidentiality, and the right to withdraw without academic consequences.

2.3. VARIABLE AND OPERATIONAL DEFINITIONS

The independent variable in this study is music conditions with three levels. The dependent variable is cognitive performance measured through three indicators: (1) accuracy, which is the percentage of correct answers calculated from the number of correct answers divided by the total of 10 questions multiplied by 100; (2) speed, which is the time to complete the task in minutes measured from the 'start' instruction until the participant hands in the answer sheet; and (3) subjective cognitive load, which is the self-report score using the

NASA Task Load Index (TLX) Indonesian version filled out immediately after completing the questions in each condition.

The selection of these three indicators is based on the empirical findings of (Lin et al., 2023), which show that music tempo not only affects answer accuracy but also cognitive processing speed. The Cognitive Load Theory also emphasizes the importance of measuring subjective cognitive load as an indicator of mental demand during a task (Evans et al., 2024). The NASA-TLX dimensions used include six sub-scales, each measured using a rating scale of 0–100 with a 5-point interval, as presented in Table 1.

Table 1. NASA Task Load Index (NASA-TLX) Dimensions

No.	Dimension	Orignal Term	Operational Definition	Measurement Scale	Score Interpretation
1.	Mental Demands	Mental Demand	How much mental and perceptual activity is required to complete the task.	0 – 100	Height = high mental burden
2.	Physical Demands	Physical Demand	How much physical activity is required during the task.	0 – 100	Height = large physical burden
3.	Time Demands	Temporal Demand	How much time pressure the participant felt.	0 – 100	Height = great time pressure
4.	Performa Performance	Performance	Participant's satisfaction level with their success.	0 – 100	Performance = poor (reverse coded)
5.	Effort	Effort	How hard the participant works mentally and physically.	0 – 100	High = a lot of effort required
6.	Frustration	Frustration	Level of insecurity, stress, and tension during the task.	0 – 100	Height = great frustration

2.4. INSTRUMENT VALIDITY

The mathematical problem-solving instrument used in this study consisted of 10 items drawn from standard junior high school mathematics textbooks (buku paket) that are officially adopted by the Indonesian Ministry of Education and Culture for Grade IX. This sourcing approach establishes content validity and face validity, as the items are aligned with the Grade IX mathematics curriculum and have been reviewed and approved through the national textbook adoption process. The items cover topics including algebraic expressions, linear equations, and basic statistical interpretation, consistent with the cognitive demands appropriate for the target population. Although formal psychometric validation (e.g., item difficulty index, discrimination index, and reliability coefficients) was not conducted in the present study, the use of curriculum-aligned items from officially sanctioned textbooks represents an accepted practice for content-valid achievement measurement in educational research contexts. Future studies are recommended to employ psychometrically validated instruments with documented reliability coefficients (e.g., Cronbach’s $\alpha \geq .70$) to strengthen the measurement quality of cognitive performance outcomes.

Data analysis was conducted using SPSS version 26.0. Before conducting inferential analysis, a comprehensive data screening was performed, which included identifying missing data using Little's MCAR test, detecting univariate outliers with a z-score criterion $> \pm 3.29$, and detecting multivariate outliers using Mahalanobis distance ($p < .001$) (Vincenzi et al., 2022). To address the research problem, Repeated Measures ANOVA (RM-ANOVA) with one within-subject factor was used, preceded by normality (Shapiro-Wilk) and sphericity (Mauchly's test) assumption checks. If the sphericity assumption was violated ($p < .05$), Greenhouse-Geisser or Huynh-Feldt corrections were applied as appropriate (Blanca et al., 2023). Post-hoc pairwise comparisons with Bonferroni correction ($\alpha = .017$) were conducted if the main effect was significant. Effect sizes were reported using generalized eta-squared ($\eta^2 g$) for RM-ANOVA and Cohen's d for pairwise comparisons. To control for initial mood and condition order effects, Repeated Measures ANCOVA was performed with PANAS scores and condition order as covariates.

3. RESULT AND ANALYSIS

3.1. DATA DESCRIPTION

This study involved 34 students as participants who followed all three experimental conditions in a within-subject repeated measures design. There were no missing data or extreme outliers detected in any of the three conditions, either through z-score detection ($|z| > 3.29$) or the IQR method, so all 34 participants were included in the statistical analysis.

Descriptive statistical summary for the three conditions is presented in Table 2. Fast music condition yields the highest average accuracy score ($M = 73.53, SD = 13.23$), followed by the NoMusic condition ($M = 67.65, SD = 13.50$), and the Slow music condition ($M = 66.76, SD = 12.24$). The average difference between the Fast and Slow conditions is 6.77 points, while the NoMusic and Slow conditions only differ by 0.89 points. The skewness values for the three conditions are within the acceptable range (±1), indicating a relatively symmetric distribution descriptively.

Table 2. Descriptive Statistics of Accuracy Scores by Music Condition (n = 34)

Condition	N	M	SD	SE	Min	Maks Max	Mdn	Skew	95% CI Lower	95% CI Atas
Slow Tempo	34	66,76	12,24	2,10	50	90	65,0	0,34	62,65	70,88
Fast Tempo	34	73,53	13,23	2,27	50	100	70,0	0,04	69,08	77,98
NoMusic (Control)	34	67,65	13,50	2,31	50	100	70,0	0,36	63,11	72,18

Note. M = mean; SD = standard deviation; SE = standard error; Mdn = median; Skew = skewness; CI = confidence interval.

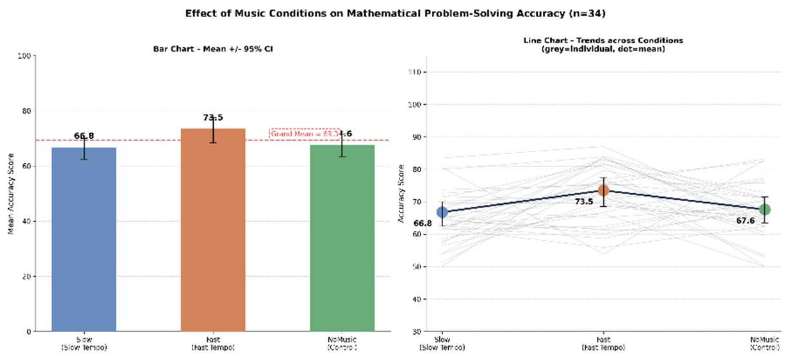

Figure 2. Comparison of Mean Accuracy Scores by Music Condition

Left: bar chart mean ± 95% CI; Right: line chart individual and mean. Error bars represent 95% confidence interval.

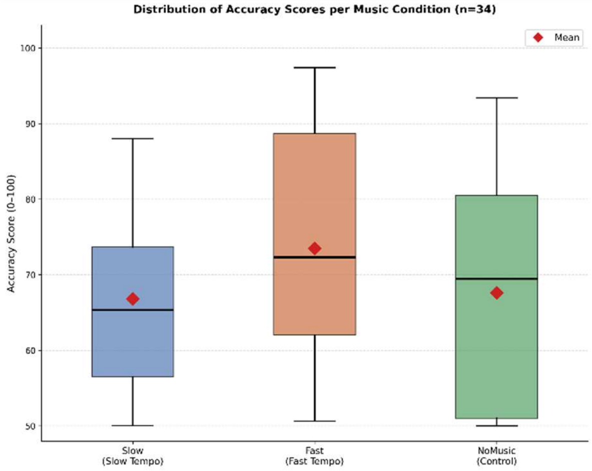

Figure 3. Accuracy Score Distribution per Music Condition (Boxplot)
The red diamond marks the mean value. There are no extreme outliers in any of the three conditions.

3.2. PREREQUISITE TEST

3.2.1. Normality Test

Normality test was conducted using the Shapiro-Wilk Test for each experimental condition. This method was chosen because it is suitable for sample sizes from small to medium (n ≤ 50) and has better statistical power compared to the Kolmogorov-Smirnov test for small samples (Mishra et al., 2019). The results of the normality test are presented in Table 3.

Table 3. Results of Shapiro-Wilk Normality Test per Music Condition

Condition	W	p	Interpretation
Slow Lambat	0,906	.007*	Not Normal
Fast Tempo	0,943	.073	Normal
NoMusic (Kontrol)	0,916	.013*	Not Normal

*Note. * p < .05 indicates non-normal distribution. W = Shapiro-Wilk statistic value.*

The Shapiro-Wilk test results indicate that the data distribution in the Slow ($W = 0.906, p = .007$) and NoMusic ($W = 0.916, p = .013$) conditions does not meet the normality assumption ($p < .05$). The Fast condition meets the normality assumption ($W = 0.943, p = .073$). Given that Repeated Measures ANOVA is robust to moderate violations of normality especially with n = 34 approaching the Central Limit Theorem threshold parametric analysis was continued (Blanca et al., 2023). As a validation, the nonparametric Friedman Test analysis was also reported.

3.2.2. Uji Sphericity

The sphericity assumption was tested using Mauchly's Test of Sphericity. The results indicate that the sphericity assumption is met, $W = 0.926$, $\chi^2(2) = 2.455$, $p = .293$. The Greenhouse-Geisser value ε = 0.931, which is close to 1.0, confirms the homogeneity of variances across conditions. Therefore, a degree of freedom correction is not required, and the F-results without correction can be used directly (Blanca et al., 2023).

3.3. MAIN ANALYSIS RESULTS

3.3.1. Repeated Measures ANOVA

Repeated Measures ANOVA analysis was conducted to test the differences in the mean scores of problem-solving accuracy across three musical conditions as a within-subject factor. The results are presented in Table 4.

Table 4. Repeated Measures ANOVA

Varians	SS	df	MS	F	p	η²g
Music Conditions	919,61	2	459,80	2,659	.078	.052
Error	11413,73	66	172,93	—	—	—

SS = sum of squares; df = degrees of freedom; MS = mean square; η²g = generalized eta-squared; Mauchly's W = 0,926, p = .293

The analysis results indicate that the main effect of music conditions is not statistically significant, $F(2, 66) = 2.659, p = .078$. Nevertheless, the obtained effect size ($\eta^2 g = .052$) falls into the medium category according to Cohen's criteria ($small = .01, medium = .06, large = .14$), suggesting that music conditions can explain around 5.2% of the total variance in accuracy scores. The effect size, which is close to being medium, suggests the presence of a substantial, albeit not yet confirmed, real effect at the conventional significance level of $\alpha = .05$.

3.3.2. Pairwise Comparison Analysis (Post Hoc)

Although the main effects were not significant, exploratory pairwise comparisons with Bonferroni correction were conducted to identify the direction of differences between the three conditions, following the recommendation for exploratory research aiming to assess effect sizes at an early stage (Lakens, 2022). The results of the analysis are presented in Table 5.

Table 5. Hasil Post Hoc Pairwise Comparison dengan Koreksi Bonferroni

Comparison	MD	SE	p (raw)	p (Bonf.)	Cohen's d	Kategori Category	Sig.
Slow vs. Fast	-6.77	2,82	.022	.067	-0.41	Small	n.s.
Slow vs. NoMusic	−0.88	3,57	.806	1,000	−0.04	Trivial	n.s.
Fast vs. NoMusic	+5,88	3,13	.069	.208	+0,32	Small	n.s.

MD = mean difference; SE = standard error; Goodbye. = Bonferroni corrected p-value; n.s. = insignificant. Cohen's interpretation d: trivial < 0.20; small 0.20–0.49; moderate 0.50–0.79; ≥ 0.80.

No pair of conditions reached statistical significance after Bonferroni correction ($\alpha = .017$). The largest mean difference was found in the Slow vs. Fast pair ($MD = -6{,}77, SE = 2{,}82, p\ Bonf. = .067, d = -0{,}41$, small effect), indicating that the Fast condition yielded a higher average score than Slow by 6,77 points. The Fast vs. NoMusic comparison also showed a similar trend ($MD = +5{,}88, d = +0{,}32, p\ Bonf. = .208$), although not significant. Conversely, the Slow vs. NoMusic comparison resulted in a very small and insignificant difference ($MD = -0{,}88, d = -0{,}04, trivial$).

3.3.3. Nonparametric Test—Friedman Test (Validation)

Given the violation of normality in two conditions, a Friedman Test was conducted as a nonparametric alternative to validate the results of the RM-ANOVA. The test results indicated $\chi^2(2) = 4.443, p = .109$, confirming no significant statistical difference among the three conditions. The consistency of results between parametric and nonparametric tests strengthens the validity of the conclusion that the effect of music conditions on accuracy scores in this study does not reach the statistical significance level at $\alpha = .05$ (Blanca et al., 2023).

3.4. TASK COMPLETION TIME

Task completion time was recorded as the duration (in seconds) each participant took to complete the mathematical problem-solving task under each condition. Descriptive statistics are presented in Table 6. The fast-tempo condition yielded the shortest mean completion time (M = 273.59 s, SD = 41.14), followed by the no-music condition (M = 320.32 s, SD = 33.96) and the slow-tempo condition (M = 335.03 s, SD = 41.18). This pattern is consistent with the accuracy results, suggesting that fast-tempo music facilitated both faster and more accurate problem-solving.

Table 6. Descriptive Statistics of Task Completion Time by Music Condition (n = 34)

Condition	N	M (s)	SD	SE	Min	Max	Mdn	95% CI Lower	95% CI Upper
Slow Tempo	34	335.03	41.18	7.06	256	440	332	320.66	349.40
Fast Tempo	34	273.59	41.14	7.06	195	359	273	259.23	287.94
NoMusic (Control)	34	320.32	33.96	5.82	272	393	310	308.48	332.17

Note. M = mean in seconds; SD = standard deviation; SE = standard error; Mdn = median; CI = confidence interval. All three conditions met the normality assumption: Shapiro-Wilk Fast W = .976, p = .638; Slow W = .985, p = .912; NoMusic W = .946, p = .092.

A Friedman test indicated a statistically significant difference in task completion time across conditions, $\chi^2(2) = 17.97$, $p < .001$. Post-hoc pairwise comparisons with Bonferroni correction showed that the Fast condition was significantly faster than the Slow condition (MD = −61.44 s, d = 1.49, p(Bonf) < .001) and the NoMusic condition (MD = −46.74 s, d = 1.24, p(Bonf) = .001). The Slow vs. NoMusic difference was not significant (MD = 14.71 s, d = 0.39, p(Bonf) = .272). These results indicate that fast-tempo music was associated with meaningfully faster task completion, consistent with the arousal hypothesis that higher auditory tempo increases cognitive processing speed.

3.5. SUBJECTIVE COGNITIVE LOAD (NASA-TLX)

Subjective cognitive load was assessed using the NASA Task Load Index (NASA-TLX), a multi-dimensional scale covering mental demand, physical demand, temporal demand, performance, effort, and frustration on a 0–100 scale, where higher scores indicate greater perceived cognitive load. Descriptive statistics are presented in Table 7. The fast-tempo condition produced the lowest mean NASA-TLX score (M = 50.07, SD = 11.17), followed by the no-music condition (M = 55.92, SD = 11.07) and the slow-tempo condition (M = 61.59, SD = 11.70), indicating that participants perceived the least cognitive burden under fast-tempo music.

Table 7. Descriptive Statistics of NASA-TLX Scores by Music Condition (n = 34)

Condition	N	M	SD	SE	Min	Max	Mdn	95% CI Lower	95% CI Upper
Slow Tempo	34	61.59	11.70	2.01	37.5	80.6	61.8	57.51	65.67
Fast Tempo	34	50.07	11.17	1.92	29.0	74.2	49.2	46.18	53.97
NoMusic (Control)	34	55.92	11.07	1.90	25.6	75.8	56.9	52.06	59.78

Note. M = mean NASA-TLX score (0–100); higher scores indicate greater perceived cognitive load. SD = standard deviation; SE = standard error; Mdn = median; CI = confidence interval.

A Friedman test indicated a statistically significant difference in NASA-TLX scores across conditions, $\chi^2(2) = 13.41$, $p = .001$. Post-hoc pairwise comparisons with Bonferroni correction showed that the Slow condition produced significantly higher perceived cognitive load than the Fast condition (MD = 11.52, d = 1.01, p(Bonf) < .001), a large effect. The Fast vs. NoMusic difference was medium in size (MD = −5.85, d = 0.53, p(Bonf) = .096) but did not survive Bonferroni correction. The Slow vs. NoMusic comparison was not significant (MD = 5.67, d = 0.50, p(Bonf) = .158). Taken together, the NASA-TLX results consistently identify fast-tempo music as the condition associated with the lowest subjective cognitive burden, corroborating the accuracy and completion time findings.

4. DISCUSSION

This study aims to examine the cognitive performance differences of class IX students under three music exposure conditions fast tempo, slow tempo, and no music, using a within-subject repeated measures design. Overall, the fast tempo music condition yielded the highest average accuracy score ($M = 73.53$) compared to the no music condition ($M = 67.65$) and the slow tempo condition ($M = 66.76$), although these differences did not reach the required level of statistical significance, $F(2, 66) = 2.659, p = .078, \eta^2 g = .052$.

This finding aligns with the direction indicated by Lin et al. (2023), who found that slow-tempo music (60–80 BPM) significantly reduces cognitive processing speed and task accuracy among college students. In this study, the Slow condition showed the lowest average accuracy ($M = 66.76$), consistent with the prediction that slow-tempo music can slow down the cognitive rhythm synchronization and lower the optimal arousal (Kiss & Linnell, 2024). Conversely, the Fast condition produced the highest average score, supporting the hypothesis that fast tempo can increase physiological arousal, which in turn facilitates faster and more accurate information processing (Lapomarda et al., 2025). This is further supported by observations that fast-tempo music can significantly affect reaction time, while slow tempo music may conversely preserve attentional efficiency (Quan et al., 2023).

Within the framework of Cognitive Load Theory (Evans et al., 2024), instrumental music without vocals, whether fast or slow, should ideally induce minimal extraneous cognitive load because it lacks semantic information competing with mathematical problem processing. However, music tempo can indirectly affect intrinsic cognitive load through the arousal mechanism: slow-tempo music that induces relaxation can lower the cognitive activation level below the optimal threshold, thus disrupting the efficiency of working memory processing (Lapomarda et al., 2025). This aligns with the Yerkes-Dodson principle, which states that optimal performance is achieved at a moderate to high level of arousal for complex cognitive tasks (Beerendonk et al., 2024).

Similar findings were also discovered in Milman & Paz-Baruch, (2025) study on teenagers with math difficulties, where music that aligned with preferences consistently improved math scores compared to silence or disliked music. Although the study operationalized the music variable differently (subjective preference vs. objective tempo), both showed that perceived enjoyable and stimulating music characteristics tend to result in better performance (Vigl et al., 2023). In this study, while preference was not explicitly controlled, the tendency for higher scores in the Fast condition can partly be explained by the fact that fast-tempo music is generally more stimulating and consistent with teenagers' music preferences, which are often exposed to genres like electronic and pop (Wei et al., 2025).

The fact that the differences between conditions do not reach statistical significance can be explained through several mechanisms. First, the limitation in statistical power due to the relatively small sample size (n = 34). Based on the obtained effect size ($\eta^2 g = .052, d = 0.41$ for the contrast Fast vs. Slow), a sample of approximately 50–60 participants is needed to achieve power of 0.80 at the $\alpha = .05$ level with three repeated measures conditions (Lakens, 2022). Second, the presence of high individual variability indicated by the large standard deviations across the three conditions (11–13 points on a 100-point scale) suggests that the response to music is highly heterogeneous among participants, aligning with the findings of Hofbauer et al. (2024) that emphasize the importance of individual factors in the effects of music on cognition. Third, the characteristics of the mathematical task used high-level reasoning problems involving integrals, exponential functions, and logarithms may demand deep concentration, which tends to reduce sensitivity to auditory stimulus differences, in accordance with the principle of selective attention, which shows that intensive cognitive focus can reduce the penetration of exogenous stimuli (Zielasko et al., 2026).

Although not statistically significant, the effect size falling within the small to medium range ($\eta^2 g = .052$; $d = 0.41$ for Fast vs. Slow) has practical relevance that cannot be ignored. In educational contexts, a 6.77-point difference in accuracy scores between the Fast and Slow conditions on a 0–100 scale can have significant implications for cumulative learning outcomes if accumulated across learning sessions (Lakens, 2022). These findings support the conclusions of Beerendonk et al. (2024) the effect of music on cognition, although statistically modest, is ecologically relevant and warrants consideration in learning environment design. Conversely, the Slow vs. NoMusic condition shows a practically trivial difference ($d = 0.04$), indicating that from a cognitive performance perspective, listening to slow-tempo music is equivalent to not listening to music at all a finding relevant to students who have traditionally used slow ambient music as background during learning sessions (Gigliotti et al., 2025).

Addressing the third study objective, this study provides empirical support for both Cognitive Load Theory and arousal-mood theory in the context of junior high school students in Indonesia. Specifically, the NASA-TLX results demonstrated that fast-tempo music significantly reduced perceived cognitive load (M = 50.07) compared to slow-tempo music (M = 61.59), $\chi^2(2) = 13.41$, p = .001, with large effect sizes for the Fast vs. Slow contrast (d = 1.01). This dissociation between accuracy (not significant) and subjective cognitive load (significant) is theoretically meaningful: fast-tempo music may reduce the mental effort experienced during problem-solving even when objective performance gains are not yet detectable at this sample size. This finding enriches the arousal-mood theory framework by showing that auditory tempo influences the subjective experience of cognitive effort independently of output accuracy. The implications for educational psychology literature include the need for replication studies with larger samples and designs integrating physiological arousal measures (heart rate, skin conductance), mood state, and music preference as mediating variables to explain the high individual variability observed in this study. The contribution of this study lies in providing the first within-subject empirical comparison of fast-tempo, slow-tempo, and no-music conditions among Indonesian junior high school students using both objective accuracy and subjective cognitive load measures, offering context-specific evidence that can inform evidence-based music use guidelines in secondary education.

5. CONCLUSION

This study examined the effects of music tempo—fast (120–190 BPM), slow (60–80 BPM), and no music—on the cognitive performance of ninth-grade (class IX) students using a within-subject repeated measures design. Three research objectives were addressed. First, regarding differences in cognitive performance across conditions: the fast-tempo condition yielded the highest mean accuracy score ($M = 73.53$), followed by the no music condition ($M = 67.65$) and the slow tempo condition (M = 66.76), with the largest difference between the Fast and Slow conditions being 6.77 points. Although this difference was not statistically significant at $\alpha = .05, F(2, 66) = 2.659, p = .078$, the effect size obtained ($\eta^2 g = .052$; $d = 0.41$) falls into the small to medium category and suggests practical relevance that should be considered. The consistency between the results of the RM-ANOVA and the Friedman Test strengthens the validity of these conclusions. Second, regarding the optimal music condition for cognitive tasks: the NASA-TLX data revealed that the fast-tempo condition produced significantly lower perceived cognitive load (M = 50.07) compared to slow-tempo (M = 61.59), $\chi^2(2) = 13.41$, p = .001, d = 1.01, indicating that fast-tempo music is the optimal condition not only for accuracy but also for subjective cognitive efficiency. Third, regarding theoretical validity: these findings provide contextual support for both Cognitive Load Theory and arousal-mood theory among junior high school students in Indonesia, demonstrating that auditory tempo modulates subjective cognitive effort even when objective accuracy differences remain below the threshold of statistical significance at this sample size.

This finding generally supports the arousal-mood theory and Cognitive Load Theory predictions that fast-paced music, which increases physiological arousal, facilitates more efficient cognitive processing on mathematical problem-solving tasks. The dissociation between non-significant accuracy differences and significant NASA-TLX differences is theoretically important: it suggests that fast-tempo music reduces subjective mental effort even before objective performance gains become detectable, consistent with the arousal-mood theory prediction that optimal stimulation lowers perceived task difficulty.

Based on these findings, class IX students are recommended to consider using fast-tempo instrumental music (120–190 BPM) as background music during mathematical problem-solving, given its advantage in both accuracy trends and subjective cognitive load reduction. Slow-tempo music is not recommended as it performed on par with silence across both measures.

6. LIMITATIONS AND FUTURE RESEARCH

This study has several limitations that should be acknowledged. First, the relatively small sample size (n

= 34) limited statistical power; a minimum of 50–60 participants is recommended for future replication to achieve power ≥ 0.80. Second, the absence of physiological measures (e.g., heart rate, skin conductance, EEG) limits the ability to explain the high individual variability observed across conditions and to confirm the arousal mechanisms hypothesized by theory. Third, the instrument used consisted of items drawn from standard mathematics textbooks, which provides face and content validity but lacks psychometric validation data such as item difficulty indices, discrimination indices, and reliability coefficients; future studies should use psychometrically validated instruments. Fourth, individual variables such as music preference, prior music exposure, and motivational state were not controlled, which may account for the wide within-condition variance. Future research should move beyond simple replication toward more theoretically ambitious designs: (1) longitudinal studies tracking the cumulative effect of music tempo on learning outcomes across multiple sessions; (2) neuroimaging or EEG studies to directly measure working memory load and arousal under different tempo conditions; (3) adaptive music systems that adjust tempo in real time based on physiological arousal feedback; (4) cross-cultural and cross-subject replication to establish boundary conditions for the tempo-cognition relationship; and (5) intervention studies testing whether sustained use of fast-tempo music during mathematics learning produces measurable gains in academic achievement over a semester. Such directions would transform this line of research from laboratory demonstrations into actionable educational technology.

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