EAI Endorsed Transactions
on Pervasive Health and Technology
Research Article **EAI.EU**

AI-Generated Emotional Background Music for Learning-Related Well-being: Task-Dependent Effects on Cognitive Performance, Workload, and Physiological State

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Abstract

INTRODUCTION: Background music is frequently incorporated into learning environments not only to enhance cognitive engagement but also to regulate learners' affective state and perceived mental effort, both of which are closely associated with learning-related well-being. However, empirical findings regarding its impact on memory performance remain inconclusive and appear to be contingent upon task characteristics as well as the emotional properties of the auditory stimulus. Recent advances in Artificial Intelligence Generated Content (AIGC) enable the parametric synthesis of music with systematically controllable emotional attributes (e.g., valence, arousal, motivational tone), thereby providing a novel methodological pathway for examining how adaptive auditory environments may support learners' cognitive functioning, stress regulation, and psychological well-being beyond the constraints of pre-composed music.
OBJECTIVES: This study investigates how emotionally differentiated AI-generated background music influences memory performance, subjective workload, and user preference within learning contexts, with particular attention to task-dependent effects across numerical and image-based memory paradigms.
METHODS: Seventeen participants completed both numerical recall and visual memory tasks under four auditory conditions: positive/motivational, soothing, focus-oriented (Low-arousal) AI-generated music, and a silence control. Behavioural accuracy was recorded alongside indicators of electroencephalography (EEG) and heart rate variability (HRV). Subjective workload and affect were assessed using the NASA Task Load Index (NASA-TLX) and the Positive and Negative Affect Schedule (PANAS).
RESULTS: Results revealed dissociable, task-dependent patterns across behavioural and psychophysiological measures. Silence yielded the highest accuracy in numerical memory tasks, whereas positive-valence music was associated with enhanced performance in image memory conditions. Distinct categories of AI-generated music also elicited differential neural and autonomic responses, suggesting variations in affective regulation and cognitive load during task execution, with focus-oriented music emerging as the most preferred auditory condition for sustained learning. Although overall behavioural accuracy remained relatively stable across conditions, emotionally parameterised AI-generated music may function as autonomy-supportive cognitive scaffolds
CONCLUSION: These findings provide preliminary evidence that AIGC-driven auditory environments may function as autonomy-supportive cognitive scaffolds that dynamically regulate stress and attentional demands during task engagement. By adaptively aligning emotional soundscapes with task characteristics and user state, AI-generated background music holds promise as a well-being-aware intervention capable of promoting cognitive sustainability and reducing perceived mental strain in digitally mediated learning systems.

Keywords: AI-Generated Music; Learning-Related Well-being; Cognitive Load; Memory Performance; Physiological Measures; Adaptive Learning Environments

Received on 03 March 2026, accepted on 15 June 2026, published on 01 July 2026

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doi: 10.4108/12075

1. Introduction

With the rapid advancement of information technology, multimedia materials, either individually or in combination, such as text, graphics, audio, and video, have become integral components of contemporary learning environments [1]. Information memory plays a central role in the learning process by supporting the encoding, storage, and retrieval of knowledge, thereby underpinning comprehension and application. During information processing, the human brain integrates inputs from multiple sensory channels. However, when visual and auditory stimuli are presented simultaneously, auditory input may interfere with visual information processing, potentially affecting cognitive performance and perceived mental effort [2]. In digitally mediated learning contexts, such cognitive–sensory interactions are increasingly associated not only with task performance but also with learners' affective state and cognitive well-being.

In this study, learning-related well-being is defined as a cognitive-affective state in which learners are able to maintain task engagement while experiencing manageable mental workload, relatively stable affect, and limited physiological strain during learning activities. This concept does not refer to long-term psychological well-being, but rather to short-term learning-state regulation reflected by subjective workload, affective experience, and physiological indicators such as electroencephalogram (EEG) and Heart Rate Variability (HRV). Accordingly, the present study treats learning-related well-being as an exploratory construct linking cognitive performance, perceived workload, emotional state, and physiological regulation.

As a ubiquitous environmental stimulus, background music has attracted increasing research attention due to its potential to influence both cognitive functioning and emotional regulation during learning tasks [3]. Existing studies suggest that background music may either facilitate or impair task performance depending on contextual factors such as task characteristics, individual differences, and the emotional attributes of the music itself [4]. While some studies have reported that emotionally positive or soothing music can improve processing speed or memory performance under specific conditions [5], others indicate that background music may act as a distractor, increasing cognitive load and reducing task efficiency [6], [7], [8]. These inconsistencies highlight the importance of task–music compatibility and suggest that the effectiveness of background music may be contingent upon the alignment between the emotional properties of auditory stimuli and task demands. Moreover, evidence for context-dependent memory effects indicates that congruency between encoding conditions and environmental cues, including auditory context, can influence memory outcomes [9]. Beyond behavioural performance, background music has also been shown to affect attentional allocation and emotional state, both of which are closely associated with perceived workload and learning-related well-being [10].

Recent advances in Artificial Intelligence Generated Content (AIGC) have introduced new possibilities for systematically investigating such interactions by enabling the parametric synthesis of music with controllable emotional attributes, such as valence and arousal [11], [12]. Prior research has demonstrated that AIGC can effectively encode affective information in visual media [13], while studies in the auditory domain have validated the emotional fidelity of Artificial Intelligence (AI)-generated music in terms of both conveyance and induction [13]. EEG-based investigations further indicate that dynamically generated music tailored to users' emotional states can regulate affective responses more effectively than static musical stimuli [15]. These developments suggest that AI-generated music may function not only as an environmental stimulus but also as an adaptive intervention capable of modulating learners' physiological and psychological states during task engagement.

Emotion constitutes a fundamental psychological variable that moderates multiple aspects of cognitive processing, including perception, attention, learning, and memory [16]. Neuroimaging studies have shown that music can activate brain regions associated with reward and motivation, such as the ventral striatum, thereby influencing affective and motivational states [17]. In conjunction with advances in multimodal emotion recognition technologies, which enable the integration of physiological and behavioural signals to infer users' emotional states, AI-generated music may be adaptively deployed to support cognitive–emotional balance during learning activities [17]. From a human–AI symbiosis perspective, such adaptive auditory environments have the potential to function as autonomy-supportive cognitive scaffolds that dynamically regulate stress and attentional demands in digitally mediated learning systems.

The distinction between numerical and picture memory tasks was grounded in working memory theory. Numerical recall primarily relies on sequential encoding and maintenance of symbolic information, which is closely related to the phonological loop and attentional control. In contrast, picture memory involves visual recognition and visuospatial processing, which may depend more strongly on the visuospatial sketchpad and perceptual discrimination. Because background music may compete with verbal–sequential processing while potentially supporting arousal or engagement during visual recognition, the effects of emotional music were expected to vary across task types.

Despite these advances, current evidence does not conclusively demonstrate that emotionally differentiated background music consistently enhances learning performance, as most existing studies focus primarily on emotional perception rather than task-related cognitive outcomes and perceived workload. Accordingly, this study examines how AI-generated background music conveying different emotional tones (e.g., positive, soothing, focus-oriented) influences memory performance, subjective workload, and physiological indicators of cognitive–affective state across distinct learning scenarios. Two representative task conditions - numerical memory and picture memory - were constructed, with the DiffRhythm music generator used to produce three emotionally distinct musical stimuli for each task alongside a no-music control condition. Participants' EEG and electrocardiogram (ECG) signals were recorded in conjunction with subjective workload assessments using the NASA Task Load Index (NASA-TLX) and mood evaluations using the Positive and Negative Affect Schedule (PANAS). By integrating behavioural, physiological, and psychological measures, this study seeks to evaluate learners' cognitive states and perceived mental workload under different music conditions and to provide empirical evidence supporting the design of well-being-aware, adaptive auditory environments for personalized learning support.

2. Research Objective

This study aims to investigate how AI-generated background music conveying different emotional tones influences learners' cognitive performance, perceived workload, and affective state during memory-based learning tasks [19]. To this end, EEG and ECG monitoring experiments were conducted within two representative task scenarios [20]: picture memory tasks and numerical memory tasks. For each task condition, three AI-generated music tracks with distinct emotional characteristics were selected to accompany task execution, while a no-music condition served as the control baseline. By comparing behavioural performance, physiological responses, and subjective evaluations across auditory conditions, this study seeks to examine the feasibility and effectiveness of emotionally differentiated AI-generated music as an adaptive auditory intervention for learning related well-being [21].

The specific research questions guiding this study are as follows:

RQ1: Does AI-generated music conveying different emotional tones influence information recall performance in learning contexts?

RQ2: How do different types of emotionally parameterised background music affect learners' subjective workload and cognitive–affective state during task execution?

RQ3: Which type of emotional background music is preferred by users for learning scenarios?

RQ4: How do users' music preferences differ between numerical memory tasks and image memory tasks?

3. Method

3.1. Experimental Variables

Independent variables: The independent variables in this study comprised:

- **Music types:** Three AI-generated emotional music types (positive, soothing, focus-oriented/low-arousal) and a no-music control condition;
- **Task types:** Numerical memory task and picture memory task.

Dependent variables: Behavioural, subjective, and physiological measures were employed to assess the effects of music condition and task type.

- **Behavioural performance:** Memory recall accuracy.
- **Subjective cognitive experience:** Task-induced fatigue and perceived cognitive workload measured using the NASA-TLX.
- **Emotional experience:** Mood states measured using the PANAS.
- **Physiological Measures:** Neurophysiological responses were assessed using EEG. Power spectral density (PSD) was extracted for the theta (4–8 Hz) and alpha (8–13 Hz) frequency bands at theoretically relevant electrode sites, including frontal (Fz), parietal (Pz), and occipital (Oz) regions. These indices were used to characterize cognitive load, attentional modulation, and cortical inhibition under different experimental conditions [22], [23]. Autonomic nervous system activity was assessed via heart rate variability (HRV) following established Task Force guidelines [24]. Time-domain metrics (e.g., RMSSD) were computed to reflect emotional regulation capacity and physiological arousal in accordance with the neurovisceral integration model [25].

Co-variates: Additional participant-level variables, including age, gender, and baseline physiological differences were treated as control factors during analysis.

3.2. Experiment Design and Participants

A 4×2 factorial experimental design with repeated measures was employed to examine the effects of AI-generated background music with different emotional tones on learners' cognitive performance and physiological responses during memory-based learning tasks. Seventeen participants were recruited from Northwestern Polytechnical University, China. Participants were aged between 20 and 25 years (M = 22.65, SD = 1.17), including nine males and eight females.

All participants reported normal hearing ability and no history of neurological or cognitive disorders. To minimize potential confounding effects associated with fatigue or sleep deprivation, participants were instructed to maintain regular sleep schedules and avoid staying up late on the day prior to the experiment. All participants confirmed that they were well-rested before participating.

Because the present study involved a relatively small sample size, the statistical analyses were interpreted with caution. The study was therefore positioned as an exploratory repeated-measures investigation intended to identify preliminary patterns rather than to provide definitive evidence of intervention efficacy. Future studies should recruit larger samples based on an a priori power analysis to verify the robustness of the observed task-dependent tendencies.

3.3. Measures

This study employed a multimodal measurement framework integrating behavioural performance metrics, neurophysiological indicators, autonomic nervous system activity, and subjective workload and affective state assessments in order to capture learners' cognitive and emotional responses under different AI-generated music conditions.

3.3.1. Behavioural Performance

Behavioural performance was quantified using recall accuracy in both numerical and picture memory tasks as an objective index of cognitive performance. In the numerical memory task, accuracy was defined as the proportion of correctly recalled digits within each 15-digit sequence presented during a trial. In the picture memory task, accuracy was calculated as the proportion of correctly identified images during similarity recognition trials. All performance scores were normalized to a range between 0 and 1 for subsequent analysis.

Each participant completed four rounds of numerical memory testing under different music conditions, with accuracy calculated for each round and averaged to obtain overall numerical memory performance. Similarly, four rounds of picture memory recognition tasks were completed, with average accuracy across trials representing visual memory performance.

3.3.2. Physiological Measurement

Neurophysiological activity during memory task execution was assessed using EEG, while autonomic nervous system regulation was evaluated using HRV derived from ECG recordings.

EEG Recording and Preprocessing: EEG signals were recorded using a wearable acquisition system with electrode placement based on the international 10–20 system standard [25]. Data acquisition focused on canonical frequency bands associated with cognitive and emotional processing, including theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (>30 Hz) rhythms.

Raw EEG data were exported and pre-processed using MATLAB with the EEGLAB toolbox [27]. Preprocessing procedures included band-pass filtering, artifact removal, and extraction of steady-state data segments. Power spectral density (PSD) was computed for each predefined frequency band [28], and averaged within selected time windows and electrode sites to quantify neural oscillatory activity under different task and music conditions. These spectral features were used as physiological indicators of cognitive load, attentional allocation, and affective modulation during learning.

HRV Measurement: HRV was used as an index of autonomic regulation reflecting emotional state and physiological arousal [29]. Time-domain HRV metrics were extracted to evaluate changes in parasympathetic and sympathetic nervous system activity under different auditory conditions. In short-duration experimental contexts involving affective stimulation, time-domain indices have been shown to capture changes in emotional and arousal states more sensitively than frequency-domain metrics [30].

In this study, the standard deviation of RR intervals (SDNN) was used to reflect overall autonomic variability, whereas the root mean square of successive RR interval differences (RMSSD) was used to characterize short-term parasympathetic regulation [31],[32]. ECG signals were recorded using the Movesense HR2 heart rate monitor at a sampling rate of 125 Hz. Inter-beat interval (IBI) sequences were exported in CSV format and analysed using Kubios HRV software.

3.3.3. Subjective Measurement

Subjective workload and affective experience during task execution were assessed using standardized self-report instruments.

The NASA-TLX: The NASA-TLX is a widely used multidimensional measure of perceived workload that evaluates mental demand, physical demand, temporal demand, task performance, effort, and frustration [33]. In the present study, NASA-TLX ratings were collected following each task to assess participants perceived cognitive load and task-related fatigue under different music conditions.

The PANAS: Affective experience was evaluated using the PANAS [33], which independently assesses positive affect (e.g., engagement, alertness) and negative affect (e.g., tension, distress). This measure was used to characterize participants' emotional responses during learning tasks across experimental conditions.

Emotion-Matching Music Validation Questionnaire: To determine whether AI-generated emotional music aligns with its intended emotions, we designed a questionnaire for Emotion-Matching Music Validation [35].

After completing the test and listening to the music, participants must select the option that best describes what they heard [36]. If a single option corresponds to the emotional music, it is considered an emotional match. Participants were asked to identify the emotional tone of each musical stimulus following exposure. Participants' demographic information such as gender, and age was also collected and incorporated in this questionnaire.

3.4. Experimental Platform

The experimental platform comprised the ErgoLAB EEG acquisition system, the Movesense ECG monitoring system, custom-designed memory task stimuli, and over-ear headphone equipment. During the experiment, emotionally differentiated background music was generated using the DiffRhythm AI music generation software, producing six musical tracks representing three distinct emotional tones (positive, soothing, and focus-oriented/low-arousal).

EEG data were acquired using the wearable ErgoLAB system, while ECG signals were recorded via the Movesense HR2 heart rate monitor. Task presentation materials were developed using Jianying (CapCut) video editing software.

3.5. Tasks and Procedure

3.5.1. Experimental Tasks

Participants completed a total of eight memory tasks (as shown in Table 1) while wearing EEG and ECG devices and listening to AI-generated music presented through headphones. Four numerical memory tasks were conducted under positive, soothing, focus-oriented, and no-music control conditions. Similarly, four picture memory tasks were conducted under positive, soothing, low-arousal, and no-music conditions.

Table 1. Experimental tasks with 8 sub-tasks in total

Task Categories	Experimental Sub-Tasks
Numerical Memory Tasks	1. Complete 15 numerical memory exercises while listening to positive music.
	2. Complete memorizing 15 numbers while listening to soothing music.
	3. Complete 15 numerical memory exercises while focusing music.
	4. Memorize 15 digits without background music.
Picture Memory Tasks	1. Complete memorization of 3 images under positive music.
	2. Complete memorizing 3 images while listening to soothing music.
	3. Complete memorization of 3 images under low-arousal music.
	4. Complete memorization of 3 images without background music.

The average duration of the background music tracks used in the numerical memory tasks was 1 minute and 55 seconds, whereas those used in the picture memory tasks averaged 1 minute and 12 seconds. Task parameters were designed based on established cognitive capacity constraints. Differences in stimulus duration (1:55 vs. 1:12) and item count (15 digits vs. 3 images) were intentional. Because people process numbers and images at different speeds, keeping the exact same duration and quantity would make one task disproportionately harder than the other. We adjusted these parameters to ensure that both tasks required a similar level of mental effort (cognitive load) from the participants. Given that working memory capacity typically supports approximately 4 ± 1 items within a 5-second temporal window, participants were required to memorize five digits every five seconds in the numerical memory tasks [37]. Each trial consisted of three consecutive digit sets (15 digits total), presented across a 15-second interval and repeated once to minimize attentional lapses. Participants subsequently reproduced the memorized sequence in written form, with recall accuracy recorded.

In the picture memory tasks, one image was presented every five seconds (three images per trial), followed by a composite image containing one or two previously presented elements. Participants were instructed to identify the matching image based on prior exposure.

3.5.2. Experimental Procedure

Pre-experiment phase: Prior to the formal experiment, a pilot study was conducted to evaluate the feasibility of the experimental protocol and optimize task timing and rest intervals.

Experiment phase: During the formal experiment, participants received a detailed briefing outlining the study's purpose, experimental procedures, and task requirements. This included instructions regarding the completion of memory tasks, subjective questionnaires, and the overall experimental workflow. The briefing ensured that participants fully understood the experimental procedures before commencing the study. Then, participants were fitted with EEG and ECG recording devices. After system calibration and confirmation of signal quality, the experimental session commenced. To mitigate potential practice and fatigue effects, the presentation order of the 8 experimental blocks (4 music conditions times × 2 task types) was systematically counterbalanced across participants using a Latin Square design. Before each task, participants listened to 30 seconds of background music corresponding to the assigned emotional condition. A brief countdown preceded task presentation, after which numerical sequences or images were displayed on screen. Following stimulus presentation, participants recorded their responses on an answer sheet. Upon completion of each task, participants completed the NASA-TLX workload questionnaire and the PANAS affect scale to document subjective experiences during task execution. A 10-minute rest interval was provided between numerical and picture memory task blocks. During the 10-minute rest interval between the numerical and picture memory task blocks, participants were allowed to rest quietly. Resting physiological signals were not systematically recorded as a formal baseline, which limits the interpretation of task-related physiological changes and is acknowledged as a limitation. This sequence was repeated until all eight tasks were completed. See Figure 1.

3.6. Ethical Statement

This research was approved by the Ethics Review Board of the Northwestern Polytechnical University (202502070). We gained informed consent from all participants. Before the experiment, the researcher explained the study and presented information regarding the research aim, activities, time investment, and benefits. The researcher also carefully explained the study setup and answered the participants' questions. The procedures used in this study adhere to the principles of the Declaration of Helsinki.

4. Results

Descriptive statistics were first calculated for behavioural accuracy, NASA-TLX, PANAS, EEG, and HRV measures. Where applicable, repeated-measures analyses of variance were conducted with auditory condition and task type as within-subject factors. For each inferential test, F values, degrees of freedom, p values, and partial eta squared values were reported. When the assumption of sphericity was violated, Greenhouse-Geisser correction was applied. Post-hoc pairwise comparisons were adjusted using Bonferroni correction. Given the exploratory nature of the study and the small sample size, statistical findings were interpreted cautiously, with emphasis placed on effect patterns rather than definitive causal claims.

4.1. Results of Emotion-Matching Music Validation Questionnaire and Behavioural Performance

Task accuracy of numerical and picture memory tasks: Across different task conditions, the Picture 1 session yielded the highest recall accuracy (M = 0.941), whereas the Picture 2 block exhibited the lowest performance (M = 0.582), indicating the greatest task difficulty. Correlation analysis revealed no statistically significant association between participants' age and memory performance across any of the experimental tasks (all $p > 0.05$). See Table 2.

Results of Emotion-Matching Music Validation Questionnaire: With the exception of low-arousal music, which had a correct identification rate below 95%, the correct identification rates for all other musical modes exceed 95%.

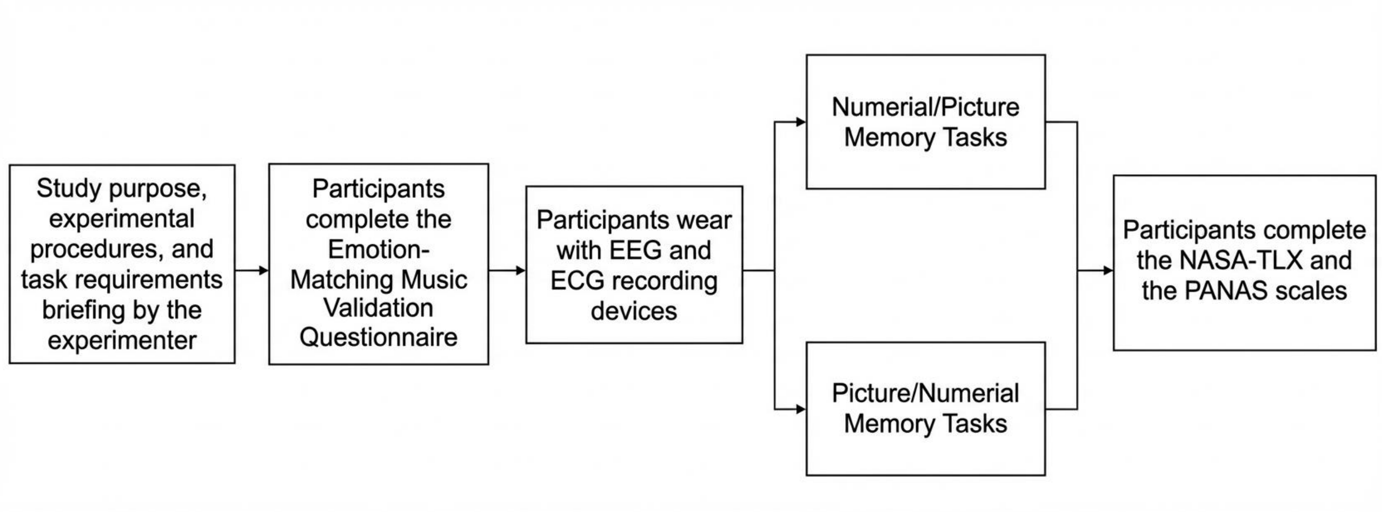

Figure 1. Experimental procedure

Table 2. Task accuracy of numerical memory tasks and picture memory tasks

Variable	Mean (SD)	Correlation(r)	P-value
Age (years)	22.65 (1.17)	——	——
[Numerical Memory Tasks]	Accuracy		
Q1(positive music)	0.718(0.223)	-0.378	0.135
Q2(soothing music)	0.804(0.191)	0.279	0.279
Q3(focusing music)	0.820(0.214)	0.060	0.818
Q4(no music)	0.906(0.115)	0.257	0.319
[Picture Memory Tasks]	Accuracy		
A-Picture 1 (positive music)	0.941(0.161)	0.208	0.422
B-Picture 2 (soothing music)	0.582(0.234)	0.340	0.182
C-Picture 3 (low-arousal music)	0.735(0.348)	-0.386	0.126
D-Picture 4 (no music)	0.882(0.273)	0.056	0.831

Results of behavioural performance: Behavioural performance was quantified using accuracy rates for the numerical memory task (Q1-Q4) and the image memory task (A-D). Overall, participants achieved a slightly higher and more stable accuracy in the numerical task (mean ± SD: 0.812 ± 0.103) compared with the image task (0.785 ± 0.138). Across numerical blocks, accuracy showed an increasing pattern from Q1 = 0.718 (lowest) to Q4 = 0.906 (highest), suggesting a potential practice effect and/or block-level difficulty differences. In the image task, accuracy varied more markedly across blocks, with A = 0.941 (highest), D = 0.882, C = 0.735, and B = 0.582 (lowest), indicating larger inter-individual variability and a particularly difficult B block, likely due to stronger similarity interference or higher discrimination demands. Above results suggest that numerical recall was comparatively more consistent, whereas image recognition accuracy was more sensitive to block characteristics and individual differences.

4.2. Results of EEG Analysis

To investigate changes in emotion, memory, and cognition across different music genres, EEG data primarily collected theta waves from the frontal lobe (Fz, F3, F4), alpha waves [38] from the occipital lobe (Oz), parietal lobe (Pz), and frontal lobe (Fz, Fp1), beta waves [39] from the frontal lobe (Fpz, F3, F4, F7, F8), and central regions (Cz, C3, C4), as well as gamma waves [40], [41].

During the picture memory task, AI-generated music exerted its most prominent neural modulation over the occipital visual cortex. Specifically, both soothing and positive music conditions were associated with significantly increased alpha power (8–13 Hz) at the Oz electrode compared to the no-music condition ($p = 0.031$ and $p = 0.011$, respectively). Increased alpha activity in visual cortical regions is commonly interpreted as reflecting enhanced cortical inhibition and reduced perceptual tension [42]. This pattern suggests that background music may have contributed to a more relaxed neural processing state during visually demanding tasks without increasing visual processing demands.

In contrast, during the numerical memory task, alpha power at the Pz electrode—often associated with emotional arousal and attentional alertness—did not exhibit significant changes under soothing music compared to the no-music condition ($p = 0.816$). See Figure 2. This finding may reflect the engagement of a task-dependent cognitive shielding mechanism; whereby neural resources are preferentially allocated to task-relevant processing under higher cognitive load while responsiveness to background auditory stimuli is attenuated.

Consistent with this interpretation, frontal theta activity (4–8 Hz) at the Fz electrode, a well-established index of cognitive load, did not show significant elevation across different music conditions (all $p > 0.05$). This suggests that AI-generated background music did not impose additional working memory or attentional demands during memory task execution. As shown in Figure 3.

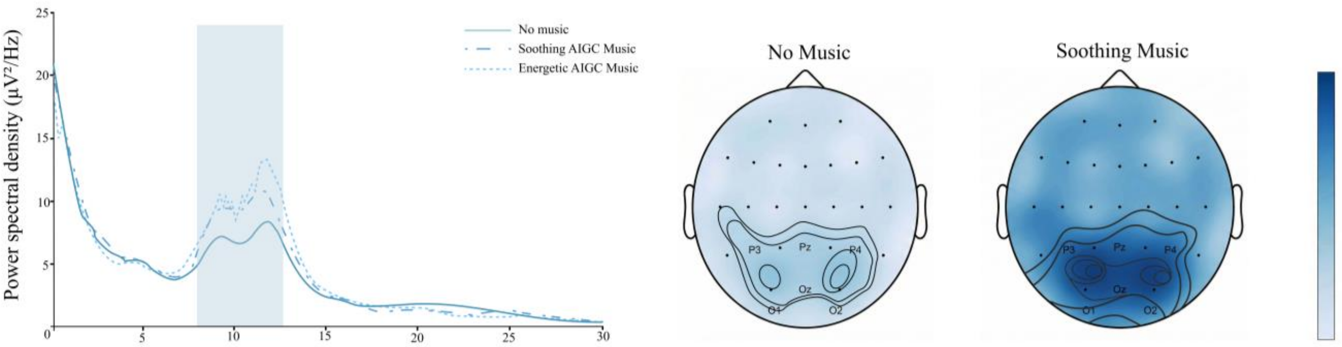

Figure 2. EEG power spectrum and scalp distribution of alpha activity under background music conditions

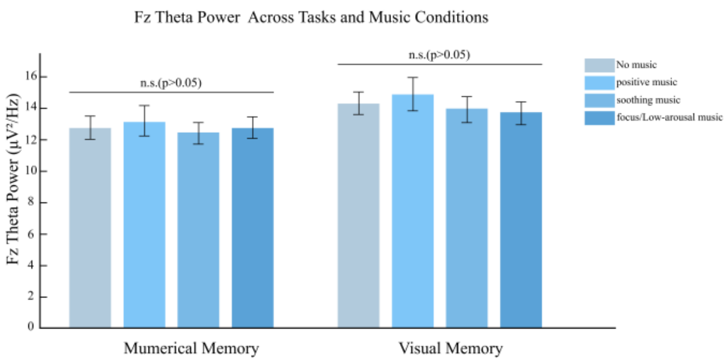

Figure 3. Fz Theta power across tasks and music conditions

4.3. Results of HRV Analysis

HRV analysis was conducted to examine autonomic nervous system responses under different emotional background music conditions during memory task execution. Time-domain HRV metrics, including SDNN and RMSSD, were compared across eight experimental conditions to evaluate changes in physiological regulation associated with music type and task demand.

In the numerical memory task, SDNN values were highest under the soothing music condition and significantly exceeded those observed under both positive and focus-oriented music ($p < 0.05$), suggesting enhanced autonomic stability in the presence of low-arousal auditory stimulation. Similarly, RMSSD values peaked under soothing music, whereas positive music was associated with slightly higher RMSSD than low-arousal music.

In the picture memory task, soothing music also yielded the highest SDNN and RMSSD values. However, differences among the positive, focus-oriented, and low-arousal music conditions were not statistically significant. These findings indicate that soothing music consistently promoted greater parasympathetic activity across task types, reflecting a more physiologically relaxed state during task engagement.

Comparison between task execution phases and post-task rest periods revealed that SDNN values during rest were significantly higher than those recorded during task performance under all music conditions ($p < 0.05$), indicating that memory tasks were associated with reduced autonomic variability. Concurrently, RMSSD during the rest phase was slightly higher than during task execution under soothing music and significantly higher than RMSSD under the remaining music conditions. This suggests that soothing music may partially buffer task-induced autonomic strain by maintaining parasympathetic activation during cognitively demanding activities [43]. The detailed data are shown in the Figure 4.

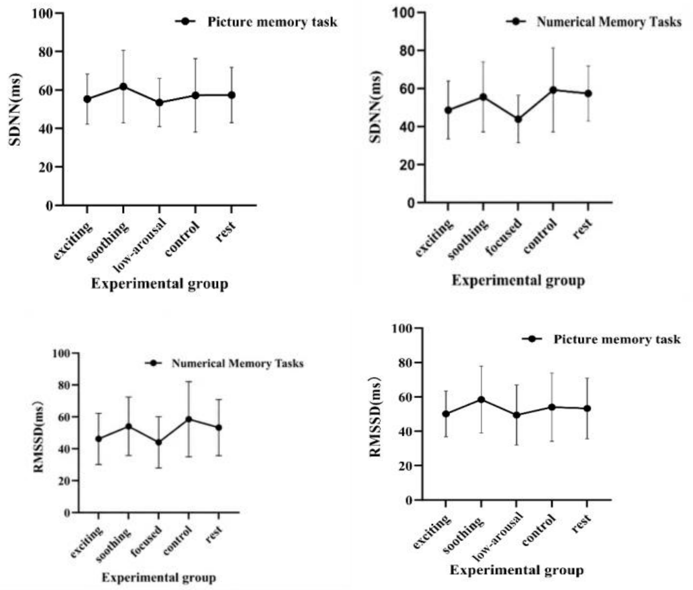

Figure 4. Comparison of Heart Rate Variability (HRV) under different background music conditions.

4.4. Results of the NASA-TLX Scale

A total of 136 valid NASA-TLX responses were collected across all experimental conditions to assess participants' perceived workload under different AI-generated music scenarios. Overall, subjective workload was primarily driven by mental demand and temporal demand, with cognitive demand yielding the highest average score (M = 4.62/7), followed by time demand (M = 4.28/7) and effort (M = 4.30/7). As shown in Table 3. Task performance ratings were moderately high (M = 4.38/7), whereas physical demand (M = 1.54/7) and frustration (M = 2.12/7) remained comparatively low. These findings suggest that task load in the present study was predominantly cognitive in nature, with minimal physical strain or negative emotional burden.

Analysis of workload dimension rankings further indicated that mental effort was identified as the primary source of task load by the majority of participants (77.54% ranked it first), while time pressure was most frequently ranked second (55.8%). This pattern is consistent with the cognitively intensive characteristics of memory-based learning tasks and supports the interpretation that subjective workload was primarily associated with cognitive–temporal processing demands rather than emotional distress.

Comparative analysis across experimental conditions revealed task-dependent differences in perceived workload under varying music types. In the numerical memory task, overall cognitive demand was higher than in the picture memory task, particularly under the positive/motivational music condition, which was associated with elevated subjective ratings of mental demand and temporal pressure.

This suggests that emotionally arousing background music may amplify perceived cognitive strain during tasks requiring sustained working memory and sequential processing.

In contrast, picture memory tasks exhibited relatively lower mental workload across most music conditions, although the no-music control condition showed a slight increase in perceived physical demand. Across all dimensions, individual variability in workload ratings remained within a moderate range (0.921–1.700), with time demand exhibiting the greatest dispersion (SD = 1.700), indicating variability in participants' sensitivity to time pressure during task execution.

Thus, AI-generated background music may influence learners' perceived cognitive load in a task-dependent manner. While behavioural accuracy remained relatively stable across conditions, emotionally differentiated music appeared to modulate subjective workload and perceived task demands, thereby shaping the cognitive–affective learning environment. This pattern provides empirical support by indicating that the impact of AI-generated background music on learning may manifest primarily through changes in perceived mental effort rather than observable performance outcomes.

Table 3. Descriptive statistics for each dimension of the NASA-TLX scale

Title	N	Mean	SD	SWM(=SEM)	95%CI
Mental demands	136	4.623	1.510	0.129	[4.369, 4.877]
Physical demands	136	1.543	0.921	0.078	[1.388, 1.699]
Time requirements	136	4.283	1.700	0.145	[3.996, 4.569]
Task performance	136	4.377	1.525	0.130	[4.120, 4.633]
Level of effort	136	4.297	1.506	0.128	[4.044, 4.551]
Frustration	136	2.116	1.415	0.120	[1.878, 2.354]

4.5. Results of the PANAS Affect Scale

A total of 136 valid PANAS responses were collected (one incomplete response from the initial 137 collected was excluded) across eight task conditions to assess participants' affective experience during task execution under different AI-generated music environments. Overall emotional intensity remained within a low-to-moderate range (overall mean score M = 2.04/5), indicating that the experimental tasks were generally experienced as cognitively engaging without eliciting pronounced negative emotional responses. See Figure 5.

Positive affect–related items showed relatively higher ratings across conditions, with absorbed (M = 3.48) and interested (M = 3.10) ranked as the most prominent emotional states, followed by excited (M = 2.83), inspired (M = 2.65), enthusiastic (M = 2.56), and determined (M = 2.52). In contrast, negative affect–related items—including fearful (M = 1.19), hostile (M = 1.20), irritable (M = 1.25), alarmed (M = 1.30), guilty (M = 1.38), and ashamed (M = 1.35)—remained consistently low across task and music conditions. These findings suggest that the use of emotionally differentiated AI-generated music did not induce substantial negative emotional responses during learning tasks.

Across all eight experimental conditions, ratings of interest and focus remained relatively high, indicating that participants maintained engagement and attentional involvement regardless of background music type. A slight increase was observed in items such as nervous (M = 2.17), which may reflect task-related cognitive pressure rather than music-induced emotional distress.

The PANAS results reveal a consistent affective pattern characterized by relatively elevated positive engagement and low negative affect. This suggests that AI-generated background music may regulate learners' emotional state during task engagement without inducing affective overload or stress responses. When considered alongside the NASA-TLX findings, these results provide additional support by indicating that emotionally parameterised music primarily modulates the cognitive-affective environment of learning tasks such as engagement and perceived strain rather than directly influencing behavioural performance outcomes.

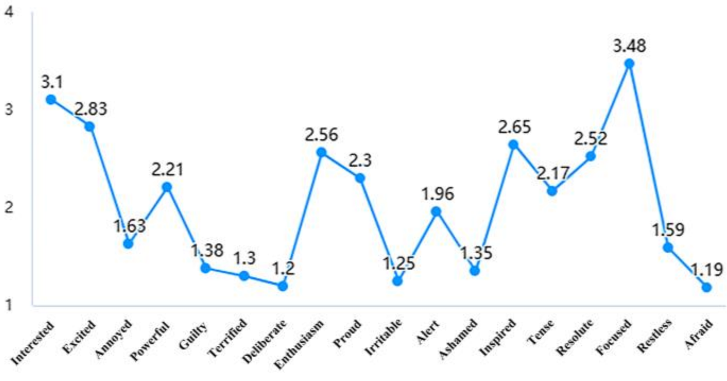

Figure 5. Average scores for each dimension of PANAS affect scale

5. Discussion

5.1. Key Findings Overview: Task-Dependent Cognitive–Affective Modulation by AI-Generated Music

By integrating behavioural accuracy, subjective workload (NASA-TLX), affective state (PANAS), and physiological indicators (HRV and EEG), this study suggests that AI-generated background music conveying different emotional tones can modulate learners' psychophysiological state during task engagement in a task-dependent manner.

Across conditions, memory accuracy remained relatively stable, indicating that emotionally differentiated background music did not consistently enhance or impair learning performance at the behavioural level (RQ1). However, more pronounced differences emerged in subjective workload, emotional engagement, and autonomic and neural responses (RQ2), suggesting that AI-generated music primarily influences the internal cognitive–affective environment in which learning occurs rather than directly improving task outcomes.

User preference data further revealed that learners tend to favour focus-oriented music for sustained learning scenarios (RQ3), while music preference exhibited systematic task-dependent shifts between numerical and picture memory tasks (RQ4). Specifically, symbolic numerical tasks appeared to benefit from reduced external stimulation, whereas visually driven tasks were more tolerant of moderate externally induced arousal.

These findings support a task–music congruency effect in which the effectiveness and perceived suitability of emotionally parameterised background music are contingent upon the alignment between task demands and induced affective state. Rather than identifying a universally optimal music type, the present results suggest that AI-generated music may function as an adaptive auditory scaffold that regulates stress, attentional demands, and perceived workload during learning activities.

This perspective shifts the role of background music from a static environmental feature toward a task-aware, autonomy-supportive intervention capable of promoting cognitive sustainability and well-being in digitally mediated learning systems.

5.2. Main Effect and Answers to RQs

5.2.1. Answers to RQ1: Effects of Emotionally Differentiated AI-Generated Music on Information Recall Performance

The results indicate that AI-generated music conveying different emotional tones does not exert a uniform facilitating or impairing effect on memory performance across learning contexts. Instead, its influence appears to be task-dependent and mediated by the alignment between induced affective state and task demands.

In the numerical memory task that requires sustained attention, sequential processing, and working memory stability, the highest recall accuracy was observed in the no-music control condition, followed by focus-oriented music, soothing music, and motivational music. This pattern suggests that symbolic tasks involving linguistic or sequential encoding are particularly sensitive to external auditory interference. From a working memory perspective, emotionally arousing music may compete with task-relevant cognitive resources, thereby increasing attentional dispersion.

In the picture memory task that required rapid visual discrimination and recognition, motivational (high-arousal) music was associated with relatively higher recall accuracy compared to soothing music. This finding suggests that visually driven tasks may benefit from moderate levels of externally induced arousal that support alertness and perceptual readiness.

The findings indicate that the effect of emotionally parameterised background music on recall performance is contingent upon task characteristics rather than reflecting a universal facilitative or disruptive influence.

5.2.2. Answers to RQ2: Effects on Subjective Workload and Cognitive–Affective State

Although behavioural accuracy remained relatively stable across auditory conditions, more pronounced differences emerged in subjective workload and physiological regulation, indicating that AI-generated music primarily modulates the psychophysiological learning environment rather than directly enhancing performance outcomes.

NASA-TLX results showed that workload in the numerical memory task was primarily driven by mental demand and time pressure, consistent with the cognitively intensive nature of sequential recall tasks. In this context, motivational music was associated with increased perceived workload, suggesting that elevated arousal may amplify cognitive strain under high-load symbolic processing conditions.

HRV analysis further revealed that soothing music produced significantly higher SDNN and RMSSD values during the digit memory task, indicating enhanced parasympathetic activation and greater autonomic stability. However, this physiologically relaxed state did not translate into improved recall performance, suggesting that reduced stress does not necessarily correspond to increased task efficiency.

PANAS results indicated that participants maintained generally positive engagement across all music conditions, with low levels of negative affect. These findings suggest that emotionally differentiated AI-generated music may regulate affective and autonomic states during learning without imposing additional working memory demands.

5.2.3. Answers to RQ3: User Preference for Emotional Background Music in Learning Contexts

Consistent with the descriptive preference results reported above, focus-oriented low-arousal music was more frequently selected as suitable for sustained learning than the other auditory conditions.

User preference results revealed that focus-oriented music was consistently rated as the most suitable auditory condition for learning scenarios, suggesting that learners favour music that supports sustained attentional engagement without inducing excessive emotional stimulation.

Compared with motivational music which may capture attentional resources through salient rhythmic or melodic features, and soothing music which may reduce physiological arousal below task-optimal levels, focus-oriented music appears to approximate a cognitively sustainable attentional state. This balance between engagement and stability may explain its relatively high usability across learning tasks.

From a learning usability perspective, soothing music may function more effectively as a physiological relaxation tool, whereas motivational music may serve as a performance enhancer in tasks requiring heightened perceptual readiness. Focus-oriented music, by contrast, may offer a compromise between cognitive activation and affective regulation.

5.2.4. Answers to RQ4: How Do Participants' Music Preferences Change Under Numerical Memory Versus Image Memory Tasks?

The descriptive preference data suggested that participants preferred auditory conditions varied across task types. However, because the sample size was small and preference was measured using self-report responses, these findings should be interpreted as preliminary.

During numerical memory tasks, participants tended to prefer reduced external stimulation (e.g., focus-oriented music or silence). Given that numerical recall relies heavily on sustained attention and working memory capacity, emotionally salient background music may compete with limited cognitive resources, thereby increasing perceived mental effort.

Conversely, during picture memory tasks emphasizing visual-spatial processing and rapid decision-making, participants showed greater preference for motivational music. In this context, externally induced arousal may facilitate attentional engagement and perceptual readiness without significantly increasing perceived workload.

These findings support the notion that user preference for background music is shaped not only by emotional valence but also by task-specific mental demands. This underscores the need for task-aware auditory adaptation strategies in AI-generated learning support systems.

5.3. Preliminary Design Implications for AI-Generated Emotional Music in Learning Contexts

The present findings suggest that AI-generated background music should not be deployed solely on the basis of generalized emotional categorization, such as “relaxing” or “motivational”. Instead, adaptive auditory environments in learning systems may benefit from incorporating task-aware and user-aware design strategies that align emotional soundscapes with mental demands and learners’ affective states [44]. Based on the observed task-dependent modulation of subjective workload, physiological responses, and user preference, several design implications can be derived for the implementation of AI-generated music in digitally mediated learning environments [45].

5.3.1. Task-Aware Auditory Adaptation

Learning systems should distinguish between different categories of cognitive activity when deploying background music. Symbolic or linguistically intensive tasks, such as numerical recall, formula derivation, or reading comprehension, rely heavily on working memory capacity and sustained attentional control. In such contexts, emotionally salient or rhythmically complex music may compete with task-relevant cognitive resources and increase perceived mental effort [46]. Accordingly, AI-generated music intended for these tasks should prioritize cognitive preservation by minimizing rhythmic complexity, dynamic fluctuations, and melodic prominence. Visually driven tasks, such as image recognition, spatial comparison, or perceptual retrieval, may tolerate or even benefit from moderate levels of externally induced arousal. Under these circumstances, steady rhythmic structures or moderately stimulating musical features may enhance alertness and engagement without significantly increasing cognitive load.

5.3.2. Emotional Parameterisation Beyond Mood Labels

Traditional background music selection frequently relies on coarse emotional descriptors, which may conflate multiple acoustic properties such as tempo, timbre, and harmonic density. AI-generated music enables more precise manipulation of emotional dimensions, particularly valence and arousal, while maintaining relative consistency across other acoustic attributes. Designers should therefore conceptualize emotional music generation as a multidimensional parameterisation process rather than a categorical selection [47]. For instance, learning systems may benefit from reducing tempo variability in symbolic tasks to minimize attentional capture, maintaining moderate rhythmic clarity in visually intensive tasks to support alertness, and controlling dynamic range to prevent abrupt perceptual shifts that may disrupt encoding processes [48].

5.3.3. Preference-Performance Trade-Off Management

The results indicate that user preference for background music does not necessarily correspond to optimal task performance. Motivational music, for example, may be subjectively preferred in certain contexts while simultaneously increasing perceived workload in cognitively demanding tasks. Consequently, adaptive auditory systems should account for the potential divergence between user liking and cognitive efficiency. A feasible design approach is to treat music preference as a soft constraint within adaptive algorithms, balancing user satisfaction against indicators of cognitive strain such as increased workload or physiological stress.

5.3.4. Physiological Feedback Integration for Closed-Loop Regulation

Physiological indicators such as heart rate variability provide real-time insights into learners' autonomic regulation and cognitive load. Integrating such indicators into adaptive music generation frameworks may enable closed-loop auditory regulation systems capable of dynamically adjusting music intensity, tempo, or structural complexity in response to learners' internal state. When physiological strain or perceived workload increases, the system may reduce musical complexity or dynamic variation, whereas decreased engagement without excessive strain may permit gradual increases in rhythmic salience to sustain attentional focus. Such adaptive feedback loops have the potential to transform background music from a static environmental feature into an interactive cognitive support mechanism.

5.3.5. Learner-Adjustable Auditory Environments

AI-generated music may be more appropriately conceptualized as learner-adjustable auditory support rather than as an autonomy-supportive scaffold in the strict self-determination theory sense. Future systems could allow learners to select baseline emotional profiles, adjust stimulation intensity, or disable background music according to task demands. Such options may increase perceived control, but the present study did not directly measure autonomy satisfaction; therefore, claims about autonomy support should remain tentative.

5.3.6 Personalization Across Individual Differences

Individual differences in working memory capacity, musical familiarity, and learning habits may influence susceptibility to auditory distraction. Adaptive music generation systems should therefore incorporate user-specific calibration mechanisms that account for baseline sensitivity to background stimulation, habitual study-with-music preferences, and physiological responsiveness to affective stimuli. Over time, such systems may develop individualized auditory profiles that better align with users' cognitive characteristics and emotional regulation needs.

5.4. Limitations and Future Research

Several limitations should be acknowledged. First, the sample size was relatively small (N = 17), which limits statistical power and the generalizability of the findings. Therefore, the present study should be regarded as exploratory, and future research should determine sample size using a priori power analysis.

Second, although the experimental blocks were counterbalanced using a Latin Square design, practice effects, fatigue, and item-level difficulty may still have influenced behavioural performance. This is particularly important for the numerical memory task, where accuracy showed an increasing descriptive pattern across condition labels. Future studies should use larger stimulus pools, multiple equivalent task versions, and statistical models that explicitly include order and block effects.

Third, the numerical and picture memory tasks differed in stimulus duration and item structure. Although these differences reflected the distinct cognitive characteristics of symbolic recall and visual recognition, they may have introduced task-difficulty confounds. Future research should conduct independent task-difficulty calibration before the formal experiment.

Fourth, the AI-generated music stimuli were validated using the same participant sample. This procedure served as a manipulation check but cannot replace independent pretesting. Future studies should validate the emotional properties of AI-generated music using an independent sample and report acoustic features such as tempo, loudness, rhythm complexity, and dynamic range.

Fifth, individual differences, including musical training, habitual study-with-music preference, sensitivity to auditory distraction, and baseline physiological variability, were not fully controlled. Future work should incorporate these variables into mixed-effects models or individualized adaptive systems.

Finally, the present study focused on short-term laboratory memory tasks. Whether AI-generated emotional background music can support long-term learning-related well-being in real educational environments remains to be examined.

6. Conclusion

This study examined how AI-generated background music conveying different emotional tones influences cognitive performance, subjective workload, affective state, and user preference across numerical and picture memory tasks. By integrating behavioural accuracy with subjective measures (NASA-TLX, PANAS) and physiological indicators (EEG and HRV), the findings indicate that emotionally differentiated AI-generated music does not consistently enhance or impair learning performance at the behavioural level. Instead, its primary effect lies in modulating learners' psychophysiological state during task engagement.

In numerical memory tasks requiring sustained attention and working memory stability, conditions with minimal external auditory stimulation (e.g., silence or focus-oriented music) were associated with relatively higher recall accuracy and lower perceived interference. In contrast, in picture memory tasks emphasizing visual discrimination and rapid perceptual processing, moderately arousing motivational music was associated with comparatively higher performance. However, these differences were descriptive rather than robust across all measures, suggesting that background music primarily influences the internal cognitive–affective environment rather than producing consistent accuracy gains or losses.

Subjective and physiological findings further indicate that soothing music was associated with greater autonomic stability, reflected in increased HRV indices, although this physiologically relaxed state did not translate into improved memory performance. Participants generally reported sustained engagement and low levels of negative affect across conditions, suggesting that emotionally parameterised AI-generated music may regulate perceived workload and affective state without imposing additional working memory demands.

User preference results revealed a task-dependent pattern in which focus-oriented music was generally favoured for sustained learning scenarios, whereas motivational music was more acceptable in visually driven tasks. These findings suggest that the optimal auditory environment for learning is not fixed, but instead depends on the interaction between task demands and induced emotional arousal.

From a design perspective, AI-generated music offers potential advantages in controllability and adaptability compared with conventional background music. Its emotional parameters, such as valence and arousal, can be intentionally adjusted, which may support more systematic investigation of task–music compatibility. However, the present findings should be interpreted as preliminary. The study does not demonstrate that AI-generated music functions as a validated intervention or that it directly improves learning performance. Rather, it suggests that emotionally differentiated AI-generated music may shape learners' perceived workload, affective experience, and physiological regulation in ways that depend on task characteristics. Future research with larger samples, independently validated music stimuli, matched task difficulty, and more rigorous statistical modelling is needed before AI-generated background music can be confidently applied as a well-being-aware learning support tool.

Acknowledgements

This study was supported by the Humanity and Social Science Youth Foundation of Ministry of Education of China (25YJCZH048); and the Shaanxi Art Studies Planning Project of Shaanxi Provincial Department of Culture and Tourism (SYG2024017).

Authors Contributions

JW and GL contributed equally to this work. Conceptualization: JW, GL; Methodology: YF, JW, and GL; Data screening and formal analysis: JW, GL, SK and JY; Writing - original draft: JW and GL; Writing - Review and Editing: YF, LM and JC; Supervision: YF; Funding acquisition: YF. All authors read and approved the final manuscript.

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