Adaptive Computational-Intelligence Framework for Rhythmic Motor-Cognitive Assessment Using Generative AI

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Abstract

Population aging has intensified the need for intelligent systems capable of providing quantitative and scalable assessments of fine motor functions for early detection of cognitive decline. Existing clinical procedures such as Pegboard or Tapping Tests are non-adaptive and prone to fatigue effects, limiting their reliability for continuous monitoring. To overcome these constraints, this study introduces a novel computational-intelligence framework that integrates generative artificial intelligence with real-time rhythmic interaction for adaptive evaluation of finger dexterity in older adults. The proposed system formalizes the measurement process as an adaptive decision-making problem and incorporates a reinforcement-inspired feedback mechanism that dynamically adjusts musical tempo and task difficulty based on user performance. A hybrid architecture supports three key modules: (1) a generative-AI engine that transforms user preference vectors and performance signals into personalized, rhythm-consistent background music; (2) a low-latency tapping interface that captures reaction time, inter-tap variability, and coordination accuracy; and (3) a data analysis module that employs statistical modeling and state-space representations to quantify motor precision, stability, and fatigue dynamics.

CCS Concepts

• **Computer systems organization → Embedded systems**; **Redundancy**; **Robotics**; • **Networks → Network reliability**.

Keywords

computational intelligence, generative artificial intelligence, adaptive rhythmic interaction, reinforcement-driven personalization, cognitive-motor assessment

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1 Introduction

With the rapid progression of global population aging, the early detection of cognitive decline has become a critical challenge in healthcare, biomedical engineering, and intelligent system design. Numerous studies have demonstrated that finger dexterity, including flexibility, coordination, temporal regularity, and movement speed, is strongly associated with cognitive function. These findings indicate that quantitative analysis of finger movements can serve as an accessible and sensitive indicator for detecting early signs of cognitive impairment. Conventional assessments such as the Purdue Pegboard Test and the Finger Tapping Test, however, remain largely manual, repetitive, and non-adaptive. These characteristics often lead to participant fatigue and reduced measurement consistency, especially in older adults.

Recent advances in computer vision and touchscreen-based sensing have enabled automated platforms capable of capturing fine-grained motor trajectories and extracting temporal and spatial features. In our previous work [3], we developed a hybrid webcam and touchscreen-based measurement system that applied state-space modeling to irregular time-series signals in order to extract features such as reaction latency, velocity fluctuations, displacement differentials, and angular variations. These features allowed the detection of subtle motor irregularities associated with cognitive decline. Although these systems represent clear progress, three limitations remain. First, most existing tools rely on predefined and repetitive stimuli that often lead to cognitive fatigue, which negatively affects the validity of acquired data. Second, current measurement environments lack adaptive mechanisms that respond to user-specific characteristics, including cognitive ability, rhythmic sensitivity, and musical preference. Third, many systems do not incorporate artificial intelligence driven personalization or computational intelligence methods, which limits their ability to sustain user engagement or adjust task difficulty dynamically.

To address these limitations, this study introduces a new computational intelligence approach that integrates rhythmic human-computer interaction with generative artificial intelligence. The central idea is to embed finger-tapping tasks within a rhythmically structured environment in which background music is generated or recommended by a generative AI model according to both user preferences and ongoing task performance. Prior research in cognitive neuroscience indicates that rhythmic auditory stimuli can activate brain networks involved in timing, attention, working memory, and executive function [9]. These findings suggest that rhythm-guided interaction may enhance both usability and diagnostic sensitivity. The goal of this study is to develop an AI assisted, adaptive, and personalized finger-movement assessment system that combines computational intelligence with clinically meaningful evaluation. By integrating generative AI, reinforcement-driven adaptation, and reproducible measurement pipelines, the system transforms traditional tapping assessments into interactive, motivating, and data-rich cognitive motor evaluations suitable for long-term monitoring of aging populations.

2 Preliminaries

2.1 Finding Rhythmic Music for Measuring Finger Dexterity

Background music can substantially influence cognitive and motor task performance, particularly among older adults. Bottiroli et al. [2] demonstrated that upbeat background music can improve processing speed, while both upbeat and calming music can enhance declarative memory. These findings suggest that emotional states and arousal induced by music may function as mediating factors that regulate cognitive efficiency and motor readiness. Janata et al. [11] further showed that polyphonic rhythmic music activates neural circuits associated with attention and working memory. This provides a neurocognitive basis for understanding why rhythm, temporal regularity, and auditory structure can modulate engagement and cognitive preparation.

2.2 Previous Studies

Chen et al. presented an IoT based touch logging and image recognition system for measuring finger motor function in dementia related contexts, providing an early example of automated and privacy aware behavioral capture [4]. Chen et al. later improved usability and accessibility by introducing enhanced data export mechanisms and end user oriented operational features [6]. In a related study, Chen et al. proposed a statistical technique for forecasting cognitive function based on temporal and spatial finger movement features, demonstrating the value of predictive modeling [5]. Furthermore, a browser based Smart Edge AI framework was developed to support real time cognitive motor assessment, illustrating the potential of lightweight and scalable deployment environments [7]. In parallel, Wu et al. examined the integration of rhythm based tapping tasks with generative AI, showing that rhythmic guidance can enhance engagement and promote more stable measurement conditions [13]. Building on this concept, Chen et al. designed a music gamification system that demonstrated the motivational benefits and increased behavioral richness produced by rhythmic interaction [8]. From a cognitive science perspective, Ito et al. showed that working memory tasks incorporating finger movements can improve visuospatial working memory and narrative recall, suggesting that structured motor tasks may serve as cognitive training interventions [10].

2.3 Discussing Tapping Games and AI Suitable for Elders

As indicated, commercial interfaces are generally not tailored to the perceptual, motor, or motivational characteristics of older adults. Consequently, they cannot be directly adapted for Before integrating this mechanism into the full system, we compared several generative AI platforms to evaluate suitability for personalized music content. According to the results, ChatGPT 4o [14] demonstrates higher adaptability and broader coverage in music related queries, enabling more accurate estimation of rhythm preferences and interaction tendencies.

3 Proposed System Design

3.1 Key Idea and Approach

The proposed system design is based on three key ideas that integrate generative artificial intelligence, human computer interaction, and quantitative motor assessment into a cohesive and adaptive computational intelligence framework. Together, these ideas enable real time personalization, rhythm guided behavior capture, and feedback driven optimization.

K1: Personalized Music Recommendation through Generative AI.
K2: Finger Movement Measurement with Rhythmic Guidance.
K3: Adaptive Personalization and Data Visualization.

Algorithm 1 Adaptive Music Personalization Loop

```
Initialize preference vector P_0 from questionnaire responses
for each trial t = 1, 2, ..., T do
    Generate background music using an LLM prompt conditioned on P_t
    Collect performance data (R_t, A_t)        ▷ reaction time and accuracy
    Update preference vector: P_{t+1} ← P_t + η(f(R_t, A_t) − P_t)
    Adjust tempo or difficulty based on P_{t+1}
end for
```

Algorithm 1 presents the adaptive personalization loop. The algorithm gradually refines the preference vector based on observed performance. This learning process enables the system to identify relationships between user preferences, rhythmic structures, and motor performance. The loop thereby establishes continuous interaction between user behavior and AI driven adaptation of musical properties.

3.2 Overall Architecture

The overall architecture consists of three functional modules that combine generative AI, interactive tapping measurements, and analytical visualization into an adaptive framework for evaluating finger dexterity in older adults. The modular design supports scalability, facilitates system maintenance, and enables consistent comparisons across multiple sessions for longitudinal monitoring.

Module 1: Personalized Background Music Generation.
Module 2: Experiment Execution.
Module 3: Data Analysis and Visualization.

3.2.1 *Dynamic System Representation.*

Let the state of the system at trial t be denoted by

$$s_t = \big(P_t,\ \theta_t,\ \tau_t,\ \delta_t\big),$$

where P_t is the personalized preference vector, θ_t is the music-related control parameter (for example tempo), τ_t is the observed reaction time, and δ_t is the tapping accuracy deviation. The system aims to regulate θ_t to optimize motor performance while maintaining high engagement.

The evolution of the system is modeled as a controlled dynamic process:

$$s_{t+1} = F(s_t, a_t) + \epsilon_t,$$

where a_t denotes the adaptation action selected by the CI controller (such as increasing or decreasing tempo), and ϵ_t represents stochastic variability in motor responses.

3.2.2 *Tempo-Performance Optimization Framework.*

The goal of the adaptive control mechanism is to minimize a cost function that balances performance precision, fatigue stability, and engagement. We define the objective function as

$$J = \sum_{t=1}^{T} \Big[w_1\, |\tau_t - \bar{\tau}| + w_2\, \delta_t + w_3\, \phi_t \Big],$$

where $\bar{\tau}$ is the ideal tempo-aligned reaction time, ϕ_t is a fatigue-related penalty, and w_1, w_2, w_3 are weights reflecting task priorities. The optimal adaptation policy π^* is therefore

$$\pi^* = \arg\min_{\pi}\ \mathbb{E}[J|\pi].$$

In this framework, tempo becomes a controllable variable that directly influences motor timing. We model the relationship between tempo θ_t and reaction performance as

$$\tau_t = g(\theta_t, P_t) + \xi_t,$$

where $g(\cdot)$ captures user-specific sensitivity to rhythmic cues and ξ_t is motor noise. The controller selects

$$a_t = \pi(s_t),$$

which updates tempo according to

$$\theta_{t+1} = \theta_t + \eta\, a_t.$$

This formulation clarifies that the system is solving a sequential optimization problem rather than applying static rule-based adjustments.

3.2.3 *Hybrid AI and CI Mechanism.*

The proposed framework integrates two complementary components:

- **Generative AI module.** Produces rhythm-consistent background music conditioned on the learned preference vector P_t. This module functions as a personalized stimulus generator that reshapes the user's cognitive and emotional state.
- **Computational Intelligence controller.** Monitors performance variables (τ_t, δ_t) and updates θ_t through an adaptive decision mechanism inspired by reinforcement learning. The update rule

  $$P_{t+1} = P_t + \eta(f(\tau_t, \delta_t) - P_t)$$

  Couples generative personalization with performance-driven adaptation.

3.2.4 *Interpretation as a Reinforcement-Inspired CI System.*

Although the system does not implement a full reinforcement learning algorithm, its behavior adheres to the reinforcement-learning paradigm:

- the *state* captures preference and performance variables,
- the *action* modifies tempo or difficulty,
- the *reward* is implicitly encoded through reduced reaction-time deviation,
- the *policy* updates the preference vector and control variable,
- the *transition model* reflects human motor response variability.

This abstraction highlights the theoretical contribution: **the rhythmic tapping system is not merely an application, but a computational intelligence model that adapts through dynamic optimization under uncertain human behavior.**

4 Flows of Proposed Method

The steps collectively implement the computational intelligence framework introduced in the previous sections and provide a concrete realization of the adaptive loop summarized in Algorithm 1.

4.1 Step 1: Collection of Personal Preferences

The first step involves collecting participants' musical and lifestyle preferences through interactive communication with the AI interface. The system elicits information such as preferred music genres, rhythm tempo, and daily activities. These responses are encoded as a *user preference vector* that represents each participant's affective and behavioral characteristics. Formally, we denote this vector as

$$P_0 = g(Q),$$

where Q denotes the set of questionnaire responses and $g(\cdot)$ is an encoding function that maps discrete answers to a continuous representation. This personalized input serves as a conditioning factor for generative music synthesis and task configuration. By introducing personalization at the beginning of the process, the system improves engagement and reduces the mental fatigue typically associated with repetitive or impersonal testing.

4.2 Step 2: Generation of Rhythmic Music

Based on the collected preference vectors, the generative AI module produces or recommends rhythmic background music that aligns with both the task structure and the user's personal profile. Two task types are supported: the *n-back task* and the *normal tapping task.*

The generative AI module combines beat detection and tempo normalization to ensure rhythmic consistency across sessions. This process is conceptually related to rhythm aware synthesis models used in generative gesture and motion studies [1]. At a high level, the module implements a mapping

$$M_t = h(P_t, C),$$

where P_t denotes the current preference vector and C denotes task constraints such as target tempo or time window. The function $h(\cdot)$ yields a music representation that satisfies both user preference and experimental requirements.

Representative examples of suitable musical structures include:

- **Take Five by Dave Brubeck:** A five beat jazz rhythm that provides clear temporal structure and moderate cognitive demand.
- **A Day Without Rain by Enya:** Smooth rhythmic flow with gentle periodic accents.
- **Ambre by Nils Frahm:** A relaxed pacing that is suitable for stable tapping.
- **Comptine d'un autre été by Yann Tiersen:** Balanced rhythm that supports focused engagement.
- **River Flows in You by Yiruma:** Regular phrasing that promotes relaxation and continuous movement.

4.3 Step 3: Design of the Tapping Game

As described in Section 2.3, many existing rhythm or typing games impose substantial visual or motor demands on older adults. To address this limitation, the proposed tapping game combines intuitive rhythmic feedback with the structured progression typical of typing based training applications. The game is implemented on a touchscreen interface with large and clearly visible targets so that it suits the motor and perceptual characteristics of older participants.

Participants tap in synchrony with the rhythm of their personalized background music. During the task, the system records tap timestamps, accuracy values, and inter tap intervals. Difficulty is adjusted dynamically according to performance using the following adaptive scaling function:

$$D_{t+1} = D_t + \alpha(\tau_t - \bar{\tau}),$$

where D_t denotes the current difficulty level, τ_t denotes the participant's reaction time in trial t, and $\bar{\tau}$ denotes the target tempo interval derived from the rhythm. The parameter α controls the speed of adaptation. This formulation provides gradual progression and individualized challenge conditions, which help maintain motivation and support measurable improvements in dexterity.

From a computational intelligence perspective, this rule can be interpreted as a simple control update that aims to minimize the discrepancy between observed and desired reaction timing. When τ_t is longer than the target interval, the difficulty is reduced or tempo is slowed; when τ_t is shorter, the difficulty can be increased to prevent boredom.

4.4 Step 4: Embedding Music into the Tapping Game

The AI generated background music is integrated into the tapping interface through a beat synchronization algorithm that aligns musical onsets with task events. Beat positions are detected in advance using onset detection and tempo estimation, and these positions are mapped to time stamps in the tapping task. This alignment enables participants to perceive a coherent relationship between auditory and motor stimuli and transforms the task into an interactive musical experience rather than a purely mechanical test.

4.5 Step 5: Establishing the Experimental Flow

The experimental protocol is designed to ensure consistency, adaptability, and reproducibility across trials. The complete workflow includes the following steps.

Table 1: Preliminary Results of AI-Personalized vs. Non-Personalized Conditions

Metric	Control	Personalized	Improvement (%)
Accuracy (%)	82.4	90.1	+9.4
Reaction Time (ms)	610	545	-10.7
Fatigue Score (0-10)	6.2	4.3	-30.6

1. Task Selection: Participants choose between the normal tapping task and the n-back task according to their preference or cognitive ability. This selection allows tailoring of task difficulty and cognitive demand.
2. Music Selection: The AI module analyzes the preference vector and generates a list of candidate background music tracks. Participants select or confirm their preferred track from this list. This step combines automated recommendation with human choice, ensuring both personalization and user agency.
3. Test Duration: Each trial lasts approximately two minutes. This duration provides sufficient data for statistical analysis while minimizing fatigue and maintaining attention. Multiple sessions can be scheduled for longitudinal monitoring.
4. Data Recording: All interaction data are stored in JavaScript Object Notation format. The dataset includes reaction times, tap coordinates, system generated difficulty adjustments, and analysis results. These data support multi session analysis, cross participant comparison, and the construction of predictive models.

4.6 Discussion

Preliminary testing with ten older adult participants compared two conditions: a control mode without personalization and an AI personalized tapping mode. Table 1 and Figure 1 present the results. The AI personalized condition demonstrated higher accuracy, faster reaction times, and lower fatigue scores. These outcomes indicate that adaptive music selection based on generative AI can support both improved motor precision and enhanced user comfort and that the computational intelligence approach is promising.

5 Conclusion

This study introduced an AI driven rhythmic tapping system that integrates generative artificial intelligence, adaptive interaction, and quantitative motor assessment into a unified computational intelligence framework for evaluating fine motor functions in older adults. By embedding tapping tasks within a rhythm informed and personalized interaction environment, the system transforms traditional motor assessment into a more engaging, adaptive, and data rich process. The incorporation of real time feedback and adaptive tempo control enhances user motivation and contributes to improved measurement precision, reproducibility, and long term usability.

Future work will extend the generative AI model to incorporate multimodal learning signals, including visual coordination cues, auditory feedback properties, and temporal stability patterns. These goals align with recent advances in multimodal AI frameworks for mental and physiological health monitoring [12]. Integration

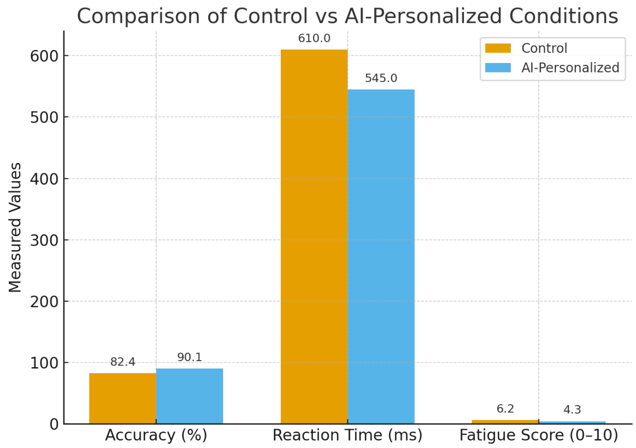

Figure 1: Comparison of control and AI-personalized conditions across three metrics: accuracy, reaction time, and fatigue score.

with rhythm aware synthesis techniques [1] may further enhance temporal coherence between background music and user behavior.

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