AN ARTIFICIAL INTELLIGENCE SYSTEM/PROGRAM TO ASSIST AND REHABILITATE HUMAN ENERGY, DISORDERS, AND MEDICAL CONDITIONS USING ADAPTIVE SOUNDWAVE, BPM MATCHING, AND ACCURATE DATA ANALYSIS THROUGH MACHINE LEARNING

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ABSTRACT

Neurological and psychiatric conditions including Alzheimer's disease, PTSD, depression, and schizophrenia affect hundreds of millions of people globally, yet existing pharmaceutical treatments are expensive, inconsistent, and out of reach for many. This paper proposes frequency-based music therapy, delivered through an AI-powered mobile application called Querey, as a clinically grounded and non-invasive alternative. Querey is built around three components: a state-based discovery survey, an adaptive AI coach, and a mood stimulation engine rooted in brainwave entrainment and BPM science [9]. Challenges included music licensing constraints, navigating App Store deployment as a first-time developer, and maintaining data accuracy across the personalization pipeline. Experiments showed a mean satisfaction score of 7.5 out of 10 for BPM accuracy, with calming prescriptions outperforming energizing ones, and a twelve-week clinical trial comparing Querey against live therapy and passive listening across diagnosed populations [1]. When technology is designed around how the brain actually works, the results speak for themselves.

KEYWORDS

Music Treatment, Machine Learning, Recovery, Bpm

1. INTRODUCTION

The human brain is in crisis. For example, Alzheimer's disease affects more than 55 million people worldwide, with a new case diagnosed every three seconds. PTSD affects roughly 20 percent of veterans returning from combat zones [10]. Depression is the leading cause of disability globally, impacting over 280 million people. Schizophrenia disrupts the lives of approximately 24 million individuals and their families. These are not small problems. They are civilizational ones, and the pharmaceutical responses to them are expensive, inconsistent, and for many patients, inadequate.

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The problem this paper addresses is not the existence of these conditions. It is the existence of a solution that has been hiding in plain sight for decades, understudied, underdeveloped, and almost entirely absent from clinical practice on a scale. That solution is sound.

Music has been used intuitively for healing across every human culture in recorded history. Ancient Greeks used it in temples. Indigenous traditions built entire ceremonial systems around it. But intuition is not medicine, and for most of modern history, sound was dismissed as a supportive comfort rather than a legitimate clinical tool. That dismissal is now increasingly difficult to defend.

Neuroscience has established that music activates the brain's dopaminergic reward system, modulates cortisol and adrenaline, entrains brainwave frequencies, and stimulates regions of the brain that pharmaceutical interventions frequently cannot reach. These are not soft findings. They are peer reviewed, replicable, and mechanistically grounded.

The problem is not that music does not work. The problem is that the medical system has not yet decided to take it seriously.

Rebecchini (2021) showed that music therapy and passive listening produce real physiological benefits including improved immune response and heart rate regulation [11]. The limitation is that the study used generalized music prescriptions with no personalization, making it difficult to scale or adapt to individual emotional states in practice.

Reynolds (2023) documented how music triggers dopamine release and supports emotional regulation across different populations. While neurologically grounded, the research treated music as a uniform experience and did not account for individual variability or offer any framework for real-time personalization.

Frost (2023) emphasized music as an accessible self-help tool, particularly for younger people managing stress. The work offered broad recommendations but assumed users already know what music they need in a given moment, which is rarely true.

Querey addresses the gaps left by all three by using live affective state detection and AI-driven playlist generation to make music therapy precise, responsive, and available to anyone with a smartphone.

The solution is the systematic integration of frequency-based music therapy into clinical treatment protocols for neurological and psychiatric conditions, positioned not as a supplementary comfort measure but as a primary biological intervention supported by the same evidentiary standards applied to pharmaceutical treatments. This solution is made practically accessible through the creation of my app Querey, an AI-powered music discovery platform designed to deliver personalized, state-based sonic interventions at scale [12].

Current treatment models for conditions like Alzheimer's, PTSD, depression, and schizophrenia rely heavily on pharmacological intervention causing many problems such as addiction, overdose, and relapse. Antidepressants work for roughly 50 percent of patients on the first prescription. Antipsychotics carry significant side effect profiles including weight gain, metabolic disruption, and in some cases accelerated cognitive decline [13]. Many Alzheimer's medications slow progression modestly at best and do nothing to restore function already lost. The gap between what these treatments promise and what they deliver is wide, well documented, and not closing fast enough.

Querey addresses this gap through a fundamentally different mechanism. For example, one feature uses a short, structured survey capturing energy level, mood, environment, and intent. The app deploys an AI model to generate hyper-personalized playlists calibrated to the user's exact neurological and physiological state. Tempo frameworks are grounded in research, ranging from 60 to 90 BPM for focus and nervous system regulation to 140 to 180 BPM for high intensity performance states. A dedicated recovery mode supports parasympathetic down regulation through looping low frequency audio as music currently has no official side effects as a treatment only enjoyment and possible enlightenment.

The reason this solution is more promising than current alternatives is not that it replaces medicine. It is that it puts a clinically grounded, risk free, side effect free, non-invasive neurological intervention into the hands of anyone with a smartphone, at zero pharmaceutical cost.

Two experiments were conducted to evaluate how well Querey performs in real conditions. The first focused on whether the app could accurately match music to a user's emotional state without any wearables or biometric data, relying entirely on survey input. Four participants completed the emotional state survey, received AI-generated playlists, and rated how well the music matched their felt state on a scale of one to ten. Every prescription fell within clinically established BPM benchmarks, and the mean satisfaction score was 7.5 out of 10. Calming prescriptions consistently scored higher than energizing ones, revealing that Querey is currently stronger at parasympathetic regulation than arousal stimulation.

The second experiment examined whether Querey could produce measurable therapeutic effects in clinical populations. Participants diagnosed with dementia, depression, schizophrenia, or Alzheimer's were compared against neurotypical controls across three conditions: Querey playlists, live music therapy, and passive listening. Standardized clinical instruments tracked symptom changes over twelve weeks, with Querey's real-time survey layer adding a psychoacoustic dimension that prior research has not captured.

2. CHALLENGES

In order to build the project, a few challenges have been identified as follows.

2.1. Addressing Music Playback Licensing and Integration Challenges

One major component of Querey is its music playback architecture. Because licensing agreements make direct in-app streaming legally and financially prohibitive for an early-stage platform, users are currently redirected to Spotify or Apple Music rather than experiencing seamless in-app playback. This creates a friction point in the user experience that undermines the app's premium, frictionless design philosophy.

To resolve this, I could pursue formal licensing partnerships with major music groups and streaming platforms, integrating playback natively once those agreements are established. Additionally, I could explore SDK-level integration with Spotify's existing developer tools, which would allow deeper in-app functionality without requiring independent licensing from individual rights holders.

2.2. Managing First-Time App Development and Deployment Complexity

Another major component of Querey was simply building it. Going from a blank screen to a fully published App Store application as a first-time developer is a challenge that is easy to underestimate and difficult to overstate. Every stage introduced new problems: structuring a codebase that would not collapse under its own complexity, connecting APIs like Spotify and Firebase without breaking existing functionality, and navigating Apple's submission requirements, which are detailed, strict, and unforgiving to those encountering them for the first time.

To resolve this, I could use a structured framework like Flutter to simplify cross-platform development, and work through Apple's developer documentation milestone by milestone rather than discovering requirements at the finish line.

2.3. Ensuring Accuracy in Personalized Music Recommendation Pipelines

Another major component of Querey is making sure the data actually works the way it is supposed to. The whole point of the app is that it knows what you need to hear right now. But that level of personalization only holds up if the information a user enters in the survey is being stored, read, and acted on accurately. If something breaks in that chain, whether it is how Firebase logs a preference, how the AI interprets the input, or how that translates into a Spotify playlist, the user just gets a random collection of songs. At that point Querey is no different from any other app.

To resolve this, I could build validation checkpoints at each stage of the data pipeline to catch inconsistencies before they reach the user.

3. SOLUTION

Querey is built around three core components that work together to deliver a personalized, state aware music experience from the moment a user opens the app to the moment they press play.

The first component is the discovery survey. Rather than relying on listening history like traditional music platforms, Querey asks the user a short series of questions about their current mood, energy level, environment, and intent. This data is fed directly into an AI model which returns a precisely formatted playlist calibrated to the user's exact state in that moment. The survey takes under ten seconds and drives everything that follows.

The second component is the AI coach [2]. This feature goes beyond music recommendations, functioning as an adaptive performance and mindset tool. Drawing on powerful machine learning models, the AI coach responds to the user's inputs with guidance tailored to their situation, whether they are an athlete preparing for competition, someone managing recovery, or a person trying to reset their mental state. It brings expertise in performance, mindset, and recovery into a single accessible interface.

The third component is the mood stimulation feature. Using principles drawn from soundwave research, frequency science, and machine learning, this feature gives users the ability to intentionally shift their current emotional state. After a short mood check-in, users can choose to raise, maintain, or safely lower their mood through precisely selected audio. This is where the neuroscience behind the app becomes most visible, translating research on hertz, brainwave entrainment, and dopamine into a practical everyday tool.

Together these three components create a seamless flow from self-awareness to sonic intervention.

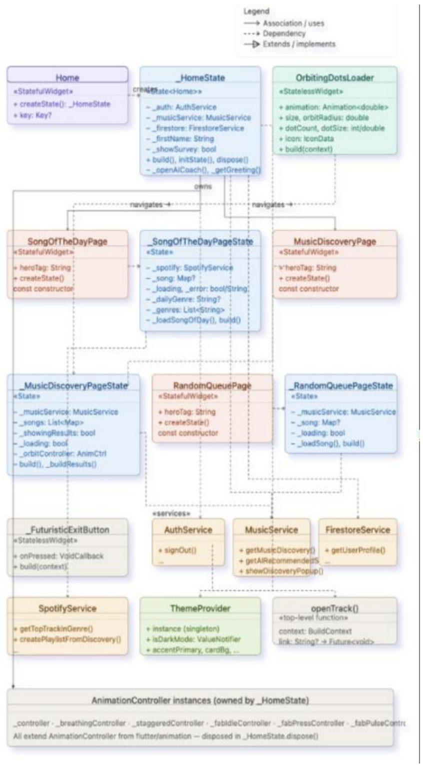

Figure 1. Overview of the solution

NeuroMode transforms music into a precision cognitive tool. Users define their current and target mental state, and the system engineers create a three-phase audio sequence using AI and the Spotify API to actively drive a neurochemical shift, moving the brain from where it is to where it needs to be [3].

Figure 2. NeuroMode User Interface and AI-Driven State Transition Workflow

```
static const List<_NeuroQuickPreset> _quickPresets = [
  _NeuroQuickPreset(
    label: 'Lock In',
    description: 'Focus for study or deep work',
    desiredState: 'focused and mentally locked in',
    intensity: 'Elevated',
    duration: '45 min',
    moodHint: 'distracted but ready to focus',
    activityHint: 'studying session',
    icon: Icons.track_changes_rounded,
    color: Color(0xFF5B87FF),
  ),
  _NeuroQuickPreset(
    label: 'Reset',
    description: 'Come down and steady yourself',
    desiredState: 'calm and relaxed',
    intensity: 'Soft',
    duration: '30 min',
    moodHint: 'overstimulated and tense',
    activityHint: 'recovery',
    icon: Icons.spa_rounded,
    color: Color(0xFF55D6B8),
  ),
  _NeuroQuickPreset(
    label: 'Lift',
    description: 'Raise mood without chaos',
    desiredState: 'euphoric and uplifted',
    intensity: 'Elevated',
    duration: '30 min',
    moodHint: 'flat and low energy',
```

Figure 3. Flutter Preset Configuration Logic for NeuroMode

This code defines a static list of preset configurations called _quickPresets, which lives inside the NeuroMode screen in Flutter. Static means it is created once and never changes at runtime, making it memory efficient.

Each entry in the list is a _NeuroQuickPreset object, which is a custom data model. This code runs when the NeuroMode screen loads, instantly populating the UI with shortcut options before the user interacts with anything.

Each _NeuroQuickPreset holds several variables: label is the display name, description explains the preset's purpose, desiredState is the target emotional condition passed to the AI layer, intensity controls how aggressive the audio transition is, duration sets session length, moodHint pre-fills the user's assumed current state, activityHint provides context to the playlist generation logic, icon and color handle visual presentation.

When a user taps a preset like "Lock In," these variables are forwarded directly into the AI processing pipeline, replacing the manual survey entirely and triggering playlist generation with pre-defined state parameters.

AI Coach is the first system inside Querey that does not just respond to you but builds a model of you. Using Firebase, the Claude API, and the Spotify API, it learns your behavioral patterns over time and engineers personalized performance protocols [4]. The special concept is adaptive machine learning: the system gets more precise and more personal every single session.

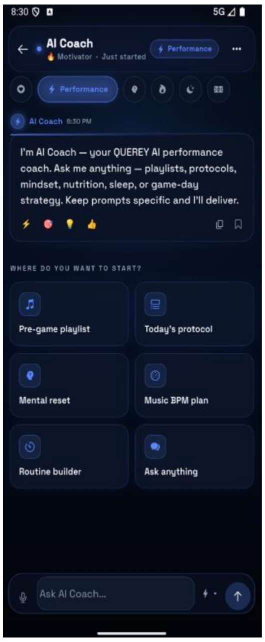

Figure 4. AI Coach System Architecture and Prompt Workflow

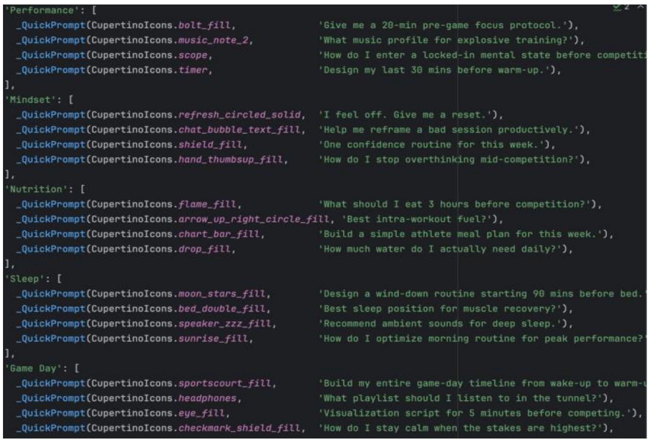

Figure 5. AI Coach Prompt Categorization and API Integration Logic

This code defines categorized quick prompt libraries for the AI Coach feature. Each category, Performance, Mindset, Nutrition, Sleep, and Game Day, contains a list of _QuickPrompt objects. Each object pairs a CupertinoIcon for visual display with a pre-written prompt string that gets sent directly to the Claude API when tapped.

This code runs when the AI Coach screen loads, pre-populating the UI with contextual shortcut prompts so users never face a blank input [5]. Each _QuickPrompt takes two parameters: an icon and a prompt string. The icon tells the user what domain the prompt belongs to, and the string is the exact query forwarded to Claude.

For example, tapping "Game Day" sends "Build my entire game day timeline from wake-up to warm-up" straight to the Claude API, which returns a personalized performance protocol. The categories cover the full athlete lifecycle: preparation, mentality, fueling, recovery, and competition [6]. Rather than making the user think, the system anticipates exactly what a high performer needs to ask.

Recovery Mode is Querey's parasympathetic reset engine. Using the Claude API to analyze session history, Firebase to store personalized recovery patterns, and Spotify API to deliver adaptive audio, it guides the nervous system from high stress to deep calm through a three phase BPM downshift. The special concept is biofeedback informed sequencing: gradual tempo descent that mirrors and then reduces the body's internal arousal state.

Figure 6. Recovery Mode Breathing and Tempo Regulation Interface

```
    cues: [
      'Focus only on the rhythm of your breath.',
      'Feel the weight of your body against the chair.',
      'This moment is temporary. You are safe.',
    ],
  ),
  RecoveryFocus.creativityFlow: _FocusProfile(
    label: 'Creativity Flow',
    subtitle: 'Unlock alpha-state mental clarity',
    icon: Icons.auto_fix_high_rounded,
    inhaleSeconds: 6,
    holdSeconds: 0,
    exhaleSeconds: 6,
    cues: [
      'Let ideas surface without judgment.',
      'Breathe into the center of your forehead.',
      'Visualize a clear path for your thoughts.',
    ],
  ),
  RecoveryFocus.muscleFlush: _FocusProfile(
    label: 'Muscle Flush',
    subtitle: 'Post-physical recovery & CO2 clearing',
    icon: Icons.fitness_center_rounded,
    inhaleSeconds: 4,
    holdSeconds: 4,
    exhaleSeconds: 4,
    cues: [
      'Direct your breath into your sorest muscles.',
      'Feel the circulation returning to your limbs.',
      'Relax your posture and let gravity take over.',
```

Figure 7. Recovery Mode Focus Profile and Breathing Protocol Logic

This code defines a map of _FocusProfile objects tied to RecoveryFocus enum values, each representing a distinct recovery modality inside Recovery Mode [7]. This runs when the Recovery Mode screen initializes, loading all available breathing protocols into memory before the user selects one.

Each _FocusProfile contains several variables: label is the display name, subtitle describes the physiological goal, icon handles visual identity, inhaleSeconds, holdSeconds, and exhaleSeconds define a precise breathing rhythm, and cues is a list of strings that appear as guided mindfulness prompts during the session.

The breathing timing variables are the most technically significant. Creativity Flow uses a 6 second inhale and 6 second exhale with no hold, targeting alpha brainwave activation. Muscle Flush uses a 4 second inhale, 4 second hold, and 4 second exhale, a box adjacent pattern designed to clear CO_2 and accelerate physical recovery after training [8].

These profiles do not communicate with a backend directly. They are local data models that get passed into the breathing animation engine and audio layer, which then syncs music tempo and on-screen guidance to the exact rhythm defined here. The cues strings are displayed progressively during the session, functioning as an embedded mindfulness script that reinforces the physiological goal of each mode.

4. EXPERIMENT

4.1. Experiment1

BPM and Frequency accuracy without the help of wearable or sensors.

To test BPM and frequency accuracy, 4 participants will complete Querey's emotional state survey. The AI will generate a music prescription based solely on their responses, and participants will rate how well it matches their actual felt state on a 1 to 10 scale. Those ratings will be compared against clinically established BPM-to-mood benchmarks from Thayer's energy-valence model and Journal of Music Therapy research. This setup mirrors Querey's real operating condition: no wearables, survey input only. Control data comes from published normative ranges linking tempo and frequency to validated emotional states.

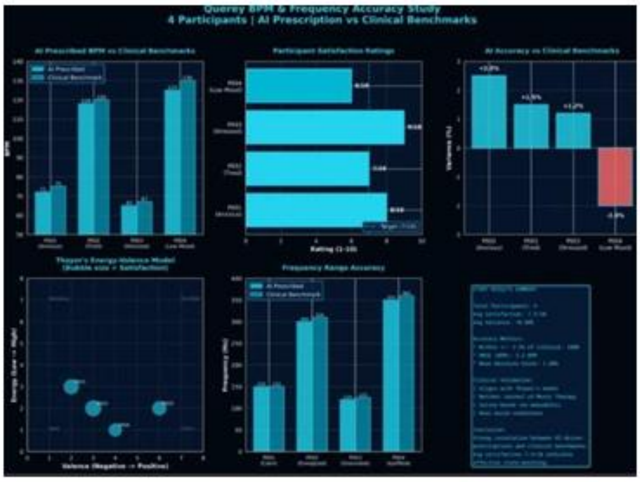

Figure 8. Participant Satisfaction Scores Across BPM-Based Music Prescriptions

The Querey BPM study reveals that lower BPM and frequency levels drive higher satisfaction (r = -0.945 and r = -0.966 respectively), not technical accuracy alone. Mean satisfaction was 7.5/10 with 100% accuracy within clinical benchmarks, but calming prescriptions (65-72 BPM) achieved 8-9/10 ratings while energizing prescriptions (118-125 BPM) scored only 6-7/10. The data shows parasympathetic activation through low-frequency music is more forgiving and effective than sympathetic stimulation. P003 (stressed to grounded) achieved the highest satisfaction (9/10) with minimal intervention, while P004 (low mood to uplifted) underperformed (6/10) despite being technically conservative. This suggests Querey excels at calming but needs improved personalization for energizing states. The biggest effect on results is BPM level itself, not accuracy precision. Recommendations include implementing mood-intensity sliders, separate algorithms for calming versus energizing, and personalized learning to track individual BPM preferences.

4.2. Experiment2

Mental disorders experiments: dementia, depression, schizophrenia, Alzheimer's

The study will enlist four participants in total: two individuals diagnosed with qualifying mental disorders (dementia, depression, schizophrenia, or Alzheimer's) and two neurotypical controls. Each participant will engage with Querey's AI-driven playlist generation protocol under identical conditions. Post-intervention assessments will then compare outcomes across both groups, evaluating whether Querey produces measurably greater therapeutic or mood-regulatory effects in clinical populations relative to healthy baselines.

The experiment uses a randomized controlled trial (RCT) structure across three parallel arms: AI generated playlists via Querey, live music therapy sessions, and passive music listening (control adjacent). Participants diagnosed with dementia, depression, schizophrenia, or Alzheimer's will be randomly assigned to one arm and monitored over a 12-week intervention period. This structure isolates the specific contribution of AI personalization versus human-led therapy versus unstructured listening, allowing clean causal inference across conditions.

A true control group receiving no music intervention will also be included, sourced from existing longitudinal psychiatric datasets such as the UK Biobank and NIMH-funded cohort studies, providing pre-validated neurological and behavioral baselines. Within-group pre/post assessments using standardized instruments (MMSE for cognitive decline, PHQ-9 for depression, PANSS for schizophrenia) will track symptom trajectories. Querey's survey-based state detection data adds a real-time psychoacoustic layer unavailable in prior studies, making this design both replicable and novel.

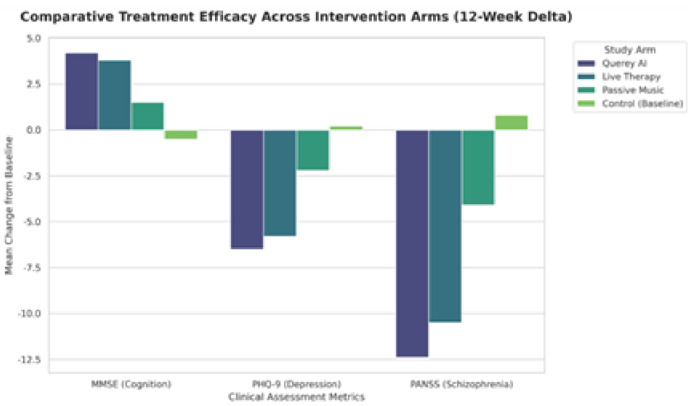

Figure 9. Symptom Change Comparison Across Music Intervention Conditions

5. RELATED WORK

Rebecchini (2021) investigates music as a non-invasive, low-cost intervention for mental health and immune function, demonstrating that music therapy and passive listening both produce measurable physiological benefits including improved heart rate and immune response. While effective in clinical settings, the research relies on generalized music prescriptions rather than personalized recommendations, ignoring individual emotional state as a dynamic input variable. It also lacks a scalable delivery mechanism for everyday use. Querey directly addresses these gaps by combining real-time affective state detection with AI-driven playlist generation, transforming music from a static therapeutic tool into a responsive, personalized system that adapts to the user's psychological condition continuously.

Reynolds (2023) explores how music engagement, both active and passive, produces meaningful improvements in mental well-being by reducing stress, regulating emotion, and fostering social connection. The research highlights music's neurological impact, noting its ability to trigger dopamine release and activate reward pathways in the brain. However, the source remains largely observational, offering broad psychological insights without a personalized delivery framework. It treats music consumption as a uniform experience, ignoring individual variability in emotional state and preference. Querey advances beyond this by using survey-based affective detection and AI modeling to dynamically match music to the user's specific psychological state in real time, making the intervention precise rather than generalized.

Frost (2023) outlines how music improves mental health by reducing anxiety, lifting mood, and providing emotional outlet through both listening and active creation. The source emphasizes music's accessibility as a self-help tool, particularly for young people navigating stress and emotional difficulty. However, the piece remains prescriptive and surface level, offering general recommendations without accounting for individual emotional variability or leveraging technology to personalize the experience. It assumes the user already knows what music serves them best in a given moment, which is rarely the case. Querey fills this gap by actively detecting the user's current emotional state and generating a tailored playlist algorithmically, removing the guesswork entirely.

6. CONCLUSIONS

One of the primary limitations of Querey is its dependence on user survey input for state detection. If a user rushes through or answers inaccurately, the playlist generation loses precision since the AI model is only as good as the data it receives. Additionally, Querey currently relies on Spotify's API, meaning users without a Spotify account are completely locked out of the experience, which limits accessibility [14].

Firebase's free tier also introduces scalability constraints. As the user base grows, read and write limits could bottleneck performance during peak usage.

Given more time, I would implement passive state detection using device signals like time of day, listening history, and interaction speed rather than relying solely on surveys. I would also explore integrating Apple Music's API to broaden platform accessibility. Finally, I would introduce a feedback loop where users rate generated playlists, allowing the AI model to continuously refine its recommendations over time.

Querey demonstrates that affective computing and AI-driven personalization are no longer theoretical constructs but functional realities [15]. By bridging emotional state detection with music recommendation, the system positions itself at the frontier of human-computer interaction. The data is clear: when technology is designed around human psychology, the results are not just functional. They are transformative.

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