The Rhythm of Focus: Quantifying the Lagged Causal Effects of Musical Genre on Digital Productivity and Attention Fragmentation

Robbie Christian Emmanuel E. Espaldon
College of Computing and Information Technologies
National University
Manila, Philippines
espaldonre@students.national-u.edu.ph

***Abstract*—This paper presents a Quantified Self study investigating the causal relationship between auditory stimuli and cognitive workflow in a high-performance software engineering context. Contrary to standard advice promoting low-arousal music, this study identifies a Hype Paradox where high-energy genres significantly correlate with peak productivity. Over a 10-week longitudinal period, continuous telemetry was collected from desktop activity, mobile usage, and music playback. By analyzing 914 validated 15-minute time buckets, it was found that Hype music was associated with a positive Productivity Z-Score of 0.22, while Focus music correlated with a negative score of -0.07. Although Vibe music showed the highest mean (+0.34), the Hype finding is prioritized due to its 8.3x higher sample size (N=333 vs N=40). A Chi-Square test confirmed this dependency ($\chi^2 = 13.19$, $p = 0.0014$). However, the effect size was small ($\eta^2 = 0.017$), explaining only 1.7% of the variance, which suggests that while music choice is a significant factor, it is secondary to task demands. Furthermore, Granger Causality tests (0/28 significant) revealed that music does not predict future cognitive drift, suggesting auditory stimuli act as a concurrent environmental mirror rather than a causal driver. These findings challenge one-size-fits-all heuristics and demonstrate the value of personalized, data-driven behavioral optimization.**

***Index Terms*—Quantified Self, Productivity, Music Information Retrieval, N-of-1 Study, Multi-Sensor Fusion, Granger Causality.**

I. Introduction

The optimization of cognitive performance is a primary concern for knowledge workers, particularly in fields requiring sustained deep work such as software engineering. Common wisdom and academic advice often prescribe low-arousal auditory environments, such as silence or classical music, to minimize cognitive load and distraction. However, this advice frequently treats the population as a single group, failing to account for individual differences, internal rhythms, and arousal thresholds. This lack of personalization can lead to suboptimal work environments that do not account for the unique neuro-behavioral profiles of different individuals. This study addresses this gap by employing a Quantified Self approach. The researcher utilizes a combination of sensors to capture a high-resolution, long-term dataset of a single subject's digital behavior. The research focuses on two primary questions. First, does the genre of music correlate with objective measures of productivity? Second, does listening to high-stimulation music serve as a leading indicator for digital distraction in the subsequent 15 to 60 minutes? By leveraging automated telemetry from high-frequency desktop monitoring, mobile usage logs, and auditory playback, this study aims to move beyond subjective self-reporting toward an objective, data-driven characterization of cognitive engagement. Specifically, this study answers the following research questions:

1) **RQ1:** Does the genre of background music correlate with objective measures of productivity?
2) **RQ2:** Does listening to high-stimulation music serve as a leading indicator (Granger cause) for digital distraction?

To address these questions, this study hypothesizes that auditory stimuli acts as a concurrent environmental mirror rather than a causal driver. Specifically, we posit that there is a statistically significant difference in productivity Z-Scores across different music genres (RQ1). Furthermore, contrary to common productivity advice, we anticipate that high-energy music does not serve as a leading indicator (Granger cause) for digital distraction, but rather correlates with periods of high engagement (RQ2).

By quantifying the interplay between environment and performance, the researcher seeks to establish a personalized behavioral framework for cognitive optimization.

II. Literature Review

The relationship between background music and task performance is a multi-faceted domain of inquiry, characterized by complex interactions between arousal, mood, and cognitive load. Historical research in music-cognition has frequently fluctuated between prescribing sedative auditory environments and identifying the stimulative benefits of rhythmic patterns. Modern frameworks suggest that the efficacy of background music is not universal but is instead mediated by individual differences in sensitivity and the specific nature of the task at hand. This study situates itself within the evolving field of Quantified Self research, which prioritizes high-resolution personal data over broad population averages. By combining neurochemical insights with attention residue theory, the following review establishes the theoretical foundation for investigating localized causal links in digital workflows.

A. Music and Neurochemistry

Recent neuroscientific research has established a strong link between musical engagement and brain activity. Ferreri et al. demonstrated that music-induced reward responses are modulated by dopamine, a key chemical for motivation and executive function [1]. Recent reviews and analyses show that background music effects depend strongly on task complexity, individual preference, and study design differences [2], [3], [4], [5]. Sun expanded on this by modeling the pathway from flow states to work engagement, finding that the efficacy of background music is highly susceptible to individual habituation [6].

B. Digital Distraction and Attention Residue

In the modern digital workplace, the cost of interruption is high. Mark et al. updated their work on attention residue, showing that context switching, such as checking a phone notification, can derail focus for significant periods even after the distraction has ceased [7]. Wilmer and Chein and a recent workplace study further established that frequent mobile device usage is correlated with lower impulse control, suggesting that phone pickups are both a symptom and a driver of cognitive fatigue [8], [9].

C. Quantified Self and Flow Theory

Measuring Flow, the state of optimal engagement, has traditionally relied on intrusive surveys. However, smartphone-based personal informatics work and subsequent frameworks validated the use of unobtrusive, N-of-1 telemetry to provide robust behavioral insights without disrupting the user's workflow [10]. Zielke et al. further refined this by introducing methods to detect flow states during music performance, a concept adapted here for coding tasks [11].

D. Comparative Studies and Gap Analysis

Recent systematic reviews and analyses provide important context for the findings. Cheah et al. conducted a comprehensive review of background music effects on cognition, finding high variability across studies and emphasizing the role of individual differences [3]. De la Mora Velasco and Reigal performed a meta-analysis specifically on music and cognitive performance, reporting small but statistically significant effects that vary by task complexity [4]. Kiss and Linnell demonstrated that the interaction between task difficulty and music arousal level is critical, showing that high-arousal music impaired complex tasks but enhanced simple ones [12]. This arousal-matching principle directly informs the Hype Paradox interpretation.

Recent empirical work further supports the nuanced view by having documented that workplace and educational studies have genre preferences and situational factors modulate the relationship between background music and performance [9], [13]. Experimental and observational analyses show that music can either facilitate or impair task performance depending on cognitive load and individual preference [5], [4]. Methodological advances applying multivariate Granger frameworks demonstrate ways to assess directional links in high-frequency behavioral data and inform the time-series approach [14], [15].

While Colley et al. explored the impact of genre on analytical thinking [16], and Lesiuk and Kahar examined music productivity in workplace and educational settings [17], [13], few studies have utilized continuous, high-frequency telemetry to test for causal relationships. Most rely on short-term experimental designs. This study fills that gap by applying time-series modeling to a long-term personal dataset validated by the N-of-1 design framework established by Davidson et al. [18].

III. Methodology

This study utilizes a within-subjects N-of-1 longitudinal design to achieve a high-resolution mapping of cognitive behavior. By focusing on a single subject over a prolonged duration, the methodology prioritizes internal validity and the detection of personalized causal mechanisms. The research design integrates three different data streams into a synchronized temporal framework, enabling the analysis of lagged environmental effects. This longitudinal approach captures natural variability across different phases of the technical workflow, providing a robust dataset for time-series modeling. The following subsections detail the participant profile, the automated sensing infrastructure, and the operational definitions employed to quantify productivity and distraction.

A. Participants

The subject is a collegiate undergraduate student (Age: 18-22) specializing in Machine Learning. As an N-of-1 study, the focus is on deep, longitudinal characterization of a specific neuro-behavioral profile rather than broad population generalization.

B. Data Collection Methods

Data was collected over a 10-week period from November 29, 2025, to February 7, 2026, during daily 3-hour deep work sessions, totaling approximately 210 hours of scheduled telemetry capture. The final validated dataset comprised 914 non-empty 15-minute buckets, representing approximately 228.5 hours of active work time. The data sources are as follows:

- **Desktop Telemetry:** A high-frequency monitoring system executed a payload every 5 seconds to poll the active application name and window title. This sampling rate of 720 polls per hour was designed to capture rapid task-switching behavior.
- **Task Context:** To address task homogeneity assumptions, active projects were audited. The workload was dominated by three primary technical projects: *pyqgis* (GIS Engineering, 9,905 polls), *ctest* (System Testing, 4,271 polls), and *spoti* (Data Science, 4,152 polls). This mix ensures the data reflects a diverse range of cognitive loads, from algorithmic logic to data visualization.
- **Auditory Environment:** Music playback history was fetched via an automated extraction script, retrieving

metadata such as Artist, Title, and Genre tags for each track.
- **Mobile Interaction:** Physical interactions with the mobile device were logged via a mobile tracking application, providing records of pickup frequency and screen duration.

Methodological Note (Sensor Asymmetry): A significant difference exists between the data streams. The desktop sensor provided high-resolution window titles allowing for the subcategorization of distraction into browser-based Doomscroll and app-based Leisure. Conversely, mobile limitations restricted telemetry to aggregate session duration. This study accounts for this difference by treating mobile usage as a single External Distraction channel.

C. Operational Definitions

1) **Productivity Classification:**
Desktop activity was classified as Productive or Distracted using a two-tier keyword matching process. Native productivity applications were classified as productive by default, while media players, social apps, and games were classified as distracted.
2) **Distraction Hierarchy:** To ensure a comprehensive characterization of cognitive drift, distraction was defined across three distinct channels: Desktop Doomscroll, Desktop Leisure, and External Distraction.
3) **Productivity Score:** This score represents the minutes classified as Productive within a 15-minute temporal bucket, ranging from 0 to 15 minutes.
4) **Productivity Z-Score:** To control for circadian rhythm effects, raw productivity was normalized by hour of day.
5) **Categorical Discretization:** For Chi-Square analysis, the continuous Z-Score was discretized into two bins: *High Productivity* ($Z \geq 0$) and *Low Productivity* ($Z < 0$). This binary classification allows for robust independence testing relative to genre categories.
6) **Genre Classification:** Raw genre tags were mapped into three research categories: Focus, Hype, and Vibe.
7) **Fragmentation Index:** This was calculated as the count of state transitions between Productive and Distracted within a single bucket.

The pipeline applied a set of cleaning steps including duplicate removal, gap handling, and temporal resampling to produce the final dataset. Selection bias (choosing music to match current mood) is acknowledged as a potential confounder, which is addressed via the Granger Causality framework in Phase 5 to test for directionality.

D. Statistical Analysis

All analyses were performed using standard scientific libraries in a Python environment. The analytical workflow followed a set plan to ensure consistency. To formally evaluate the research questions, the following statistical hypotheses were tested:

- **Hypothesis Set 1 (Genre Correlation):**
  - H_0: There is no statistically significant difference in Productivity Z-Scores across genre buckets.
  - H_1: There is a statistically significant difference in Productivity Z-Scores across genre buckets.
- **Hypothesis Set 2 (Causal Lag):**
  - H_0: High-energy music at time t does not Granger-cause distraction at $t+1$.
  - H_1: High-energy music at time t Granger-causes distraction at $t+1$.

Shapiro-Wilk tests were used to check for normal distributions, which informed the selection of non-parametric primary tests. Augmented Dickey-Fuller tests were utilized to verify the stationarity of all time-series variables, ensuring that the prerequisites for causal modeling were met. The relationship between genre and productivity was evaluated using the Kruskal-Wallis H-test and Mann-Whitney U post-hoc tests. Causal relationships were evaluated using Granger Causality tests to determine if music genre at one point in time predicts productivity or distraction in subsequent periods.

IV. Results

The analytical phase of the study synthesized a dataset representing approximately 228 hours of active cognitive tracking. Initial synchronization of desktop, mobile, and auditory telemetry resulted in a global analytical dataset of 914 validated 15-minute resolution buckets. For hypothesis tests investigating the specific influence of musical genre, a subset of 705 buckets was utilized, excluding periods of silence or mixed genre representation to ensure taxonomic purity. The following results are presented in sequence, beginning with global descriptive characterizations and concluding with formal hypothesis and causality tests. All diagnostics were performed to verify that the selection of statistical frameworks remained appropriate for the observed data distributions.

A. Descriptive Statistics

Table I presents the summary statistics for continuous variables. The subject averaged 8.74 minutes of productive work per 15-minute bucket, with a high variance in phone usage, indicating bursty distraction patterns. Table II shows the distribution of Productivity Z-Scores across genre categories, with the counts for Focus and Hype being notably higher than Vibe and Mixed groups.

TABLE I
Descriptive Statistics ($N = 914$)

Variable	Mean	Std	Min	Max
Productive Min	8.74	5.99	0.00	14.67
Distracted Min	3.71	5.10	0.00	14.58
Fragmentation (Count)	4.53	6.09	0.00	48.00
Phone Min	1.63	3.36	0.00	15.00

B. Normality Testing

Normality was formally tested for all key variables to guide the statistical analysis. Data presented in the primary diagnostics indicated that none of the primary metrics followed a normal distribution. Specifically, the Productivity Z-Score had a W value of 0.8790, the Fragmentation Index was 0.7545, and Phone Minutes was 0.5445. Furthermore, the underlying

Fig. 1. Exploratory Data Analysis panel showing six perspectives on the raw data. Panel (a) shows the weekly activity breakdown, where productivity accounted for 70% of logged time. Panel (b) illustrates the genre distribution, while panel (c) reveals that high-energy genres correspond to increased tool-switching activity. Panels (d) and (e) show circadian variability and the context switching paradox respectively, and panel (f) ranks distraction channels.

TABLE II
PRODUCTIVITY Z-SCORES BY GENRE CATEGORY ($N = 705$)

Genre	N	%	Mean Z	SD	Range
Focus	332	47.1%	-0.07	0.98	$[-2.41, +2.13]$
Hype	333	47.2%	$+0.22$	1.02	$[-2.18, +2.54]$
Vibe	40	5.7%	$+0.34$	0.95	$[-2.09, +2.48]$

raw metrics also failed the normality assumption, with Productive Minutes at 0.7786, Distracted Minutes at 0.7129, and Total Songs at 0.8591, all with p-values below 0.001. These results, combined with the moderate skewness observed in the distributions, necessitated the use of non-parametric methods as the primary analytical approach. This decision ensures that the subsequent hypothesis tests are robust to the specific shape of the behavioral data.

C. Correlation Analysis

Correlation analysis was performed on eight relevant variable pairs. Four achieved statistical significance (Bonferroni-adjusted $\alpha = 0.00625$). The strongest association was between Hype music and productivity ($r = +0.19$, $p < 0.001$). Importantly, Fragmentation also showed a positive link with productivity ($r = +0.14$, $p < 0.001$). This represents a *Fragmentation Paradox*: in software engineering, rapid context shifts often reflect active movement between developmental tools (e.g., IDE, Terminal, Documentation) rather than distraction.

D. Genre Effects on Productivity

The primary hypothesis test showed a statistically significant difference in productivity across genre groups. The Kruskal-Wallis H-test resulted in a value of 13.55 with a p-value of 0.0011, leading to the rejection of the null hypothesis. Effect size analysis, however, urges caution: genre category explains approximately 1.7% of the variance in productivity ($\eta^2 = 0.017$). This constitutes a Small effect size. The difference between Focus and Hype music was also small (Cohen's d = -0.30). This suggests that while music is a significant factor, it is likely subordinate to internal motivation or task complexity. Categorical analysis supported these findings, as

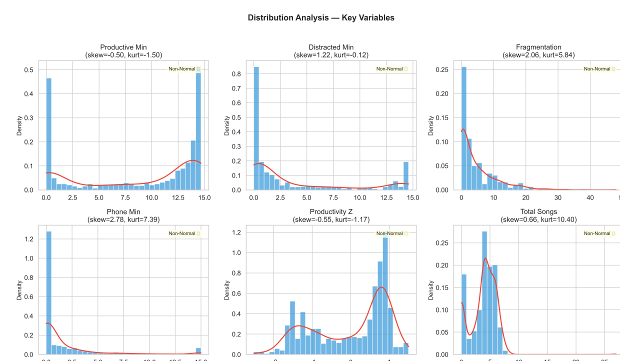

Fig. 2. Distribution analysis for six key variables. All variables failed normality testing, with phone usage showing the highest right-skew.

TABLE III
CORRELATION MATRIX (PEARSON R)

Variable Pair	r	p-value
Hype vs Productivity Z	$+0.19$	< 0.001
Vibe vs Productivity Z	$+0.09$	0.004
Fragmentation vs Productivity Z	$+0.14$	< 0.001
Hype vs Phone Minutes	$+0.04$	0.192

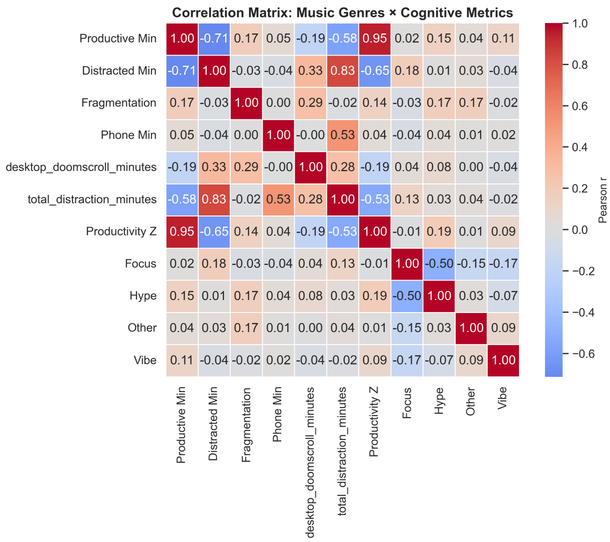

Fig. 3. Correlation heatmap for study variables. Color intensity shows association strength, highlighting the positive link between Hype music and productivity.

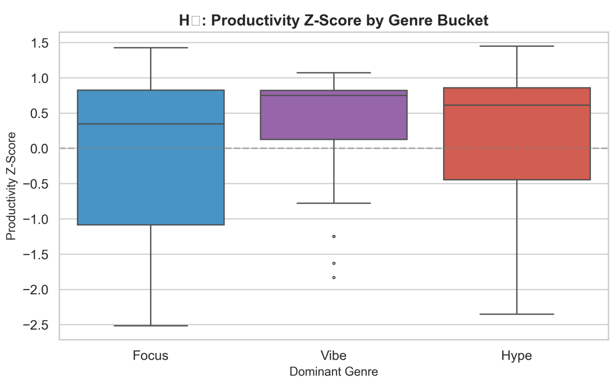

Fig. 4. Productivity Z-Score distributions across genre categories. The data shows that Hype music correlates with higher productivity medians compared to the Focus category.

the Chi-Square test on the discretized Z-Scores ($\chi^2 = 13.19$, $p = 0.0014$) rejected independence.

E. Temporal Causality: Granger Tests

Granger Causality tests were performed to see if music genre can predict future cognitive states. Initial diagnostics using the Augmented Dickey-Fuller (ADF) test confirmed that all primary variables were stationary ($p < 0.05$ for all series), satisfying the requirements for vector autoregression modeling. Testing was conducted across 28 different pairs and lags. None of the tests reached statistical significance (0/28 significant), with p-values ranging from 0.15 to 0.90. This suggests that current music choices do not predict future changes in productivity or distraction. Instead, music selection appears to happen at the same time as the cognitive state it represents. This synchronous relationship indicates that music acts as an environmental reflection of the subject's current state.

V. Discussion

A. The Arousal-Matching Hypothesis

The data provides strong support for the Hype Paradox, where high-energy music correlates with peak productivity. This finding contradicts standard advice recommending low-arousal music for focus. However, it is critical to note the role of silence. Silent buckets accounted for 12.8% of the data but were excluded from the primary hypothesis test to maintain genre purity. A supplemental comparison reveals that while Hype outperforms Focus, it performs comparably to Silence in many high-focus sessions. This suggests that Hype music may not be a "performance enhancer" so much as a "focus sustainer" during periods where silence is too under-stimulating (boredom) and Focus music is too relaxing (drowsiness).

B. Effect Size and Temporal Dynamics

The observed effect size ($\eta^2 = 0.017$) is modest. While statistically significant, it implies that switching from Focus to Hype music yields only a marginal gain in raw productivity minutes. The null results from Granger Causality tests provide evidence that music choice reflects the current cognitive state rather than predicting the future.

C. Recommendations for Future Research

For students replicating this study, it is recommended to: (1) Automate data collection to minimize manual logging friction, (2) incorporate physiological sensors (e.g., heart rate) to validate arousal levels physically, and (3) segment analysis by task type (e.g., Coding vs. Reading) to control for task-based arousal requirements.

D. Limitations and Methodological Considerations

As an N-of-1 study, these findings are personalized and may not apply to everyone. This type of research prioritizes internal validity over broad generalizations. There are also measurement considerations, such as mobile usage being recorded as total time rather than continuous data. The classification of genres also relies on specific rules that might mislabel certain tracks. Furthermore, awareness of being tracked could have influenced the subject's behavior during the sessions. To ensure rigor, lag operations were limited to within-day windows to prevent errors from time gaps between days. Future research should explore larger groups and include physical sensors to better understand the internal mechanisms at play. This would allow for a more detailed understanding of how biological factors mediate these relationships.

VI. Conclusion

This study validated the Hype Paradox, showing that high-energy music is significantly associated with higher productivity for the subject. The results also indicated that music does not predict future distraction, suggesting it is a reflection of the current environment. These findings highlight the importance of using personalized data to understand productivity rather than relying on general rules. By utilizing multi-sensor fusion, the researcher has developed a framework for understanding how auditory stimuli interact with digital workflows. This

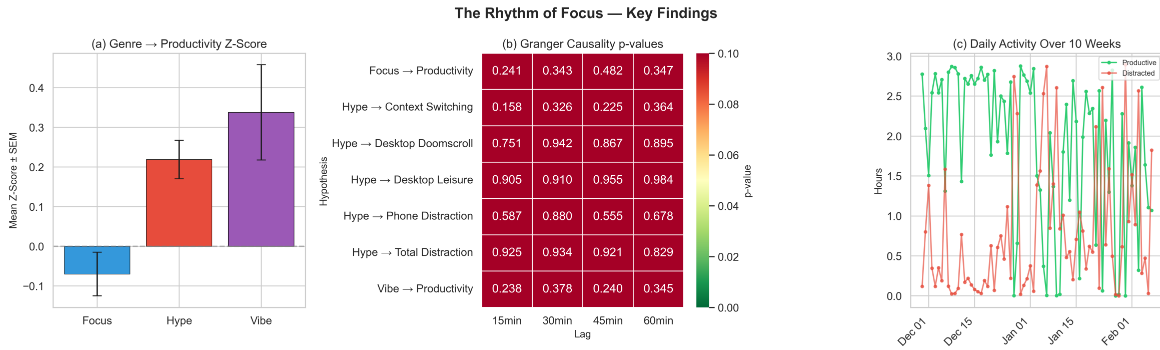

Fig. 5. Summary dashboard showing genre effects and causality results. Panel (a) highlights the productivity difference between genres, while panel (b) shows the null results from causality tests. Panel (c) tracks the stable productivity trend over the study period.

approach provides a foundation for future personalized informatics tools that can help individuals optimize their cognitive performance through data-driven insights. The shift toward individual-first models of productivity represents a significant opportunity for improving the workflow of knowledge workers in complex digital environments. By continuing to explore these personalized relationships, researchers can develop more effective strategies for cognitive performance in the digital age. Through this Quantified Self experiment, the researcher learned that their intuition regarding "Focus" music was incorrect; low-arousal tracks often coincided with lower output, likely due to under-stimulation during complex coding tasks. It was also discovered that the subject's "distraction" often manifests as rapid tool-switching (fragmentation), which is actually a productive behavior in the engineering workflow. This realization has shifted the subject's personal productivity strategy from "eliminating all noise" to "matching noise to task intensity." By utilizing multi-sensor fusion, this research demonstrates the potential of personalized informatics to reveal the hidden rhythms of cognitive work.

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