Exploring Fibonacci-Derived Temporal Clustering in Reported Synchronicity Events

2026-10-02

Author:
Rob G. Sacco

Affiliation:
Independent Researcher
Ottawa, Canada

Note:
This paper is part of an ongoing independent research archive.
It is released openly for reading and scholarly reference.

Abstract

Previous research has suggested that reported synchronicity events may cluster near Fibonacci-derived temporal intervals, but it remains unclear whether such patterns represent broad temporal correspondence or localized clustering. The present exploratory study tested whether 41 reported synchronicity events occurred unusually close to mathematically defined Fibonacci-derived age intervals. Event ages were compared continuously with five candidate temporal intervals across ±3-, ±5-, and ±10-day proximity windows, with statistical controls for the amount of temporal space covered by each model. Results identified the strongest nominal clustering within a narrow ±5-day window near the 1.668-year cumulative interval, where three events were observed compared with approximately 0.68 expected under the null model. Although this pattern yielded nominally significant exact and permutation results, it did not survive adjustment for multiple comparisons and is therefore interpreted as an exploratory candidate effect rather than confirmatory evidence. No comparable nominal effects were observed across lower or higher harmonic intervals. These findings refine a broad hypothesis of Fibonacci-derived temporal organization into a specific, falsifiable prediction concerning the cumulative 1.668-year interval within a ±5-day window. Independent preregistered replication is required to determine whether this localized pattern is reproducible.

Keywords: complex systems, constraint-based dynamics, harmonic intervals, non-equilibrium systems, synchronicity, temporal organization, temporal clustering

Contents

1. Introduction **1**
1.1 Synchronicity and the Problem of Temporal Structure 1
1.2 Fibonacci-Based Models of Temporal Organization 2
1.3 Limitations of Calendar-Based Matching Approaches 3
1.4 Present Study: A Refined Proximity-Based Framework 3
1.5 Objectives and Hypotheses 4
1.6 Conceptual Significance 5
2. Methods **5**
2.1 Participants and Data 5
2.2 Harmonic Lattice Construction 7
2.3 Distance-to-Lattice Calculation 8
2.4 Window Definition 8
2.5 Coverage-Based Expected Values 8
2.6 Statistical Analysis 9
2.7 Precision and Numerical Specification of Harmonic Intervals 9
2.8 Permutation Testing 9
2.9 Density-Matched Random-Grid Analysis 10
2.10 Direct vs. Cumulative Harmonic Construction 10
2.11 Harmonic-Specific Analysis 10
2.12 Multiple Comparisons and Exploratory Inference 10
2.13 AI-Assisted Analysis 11
3. Methodological Comparison with Prior Study **11**
3.1 Time Representation 11
3.2 Personalization vs. Universal Lattice 11
3.3 Matching Criterion 12
3.4 Window Structure 12
3.5 Lattice Composition 12
3.6 Statistical Baseline 12
3.7 Harmonic Structure 12
3.8 Conceptual Shift 13
3.9 Additional Validation Procedures 13
4. Results **13**
4.1 Relationship to Prior Broad-Window Findings 13
4.2 Emergence of a Candidate Narrow-Band Pattern Under High-Resolution Analysis 14

4.3 Harmonic Component Decomposition and Robustness 14
4.4 Localized Harmonic Alignment 15
4.5 Permutation Validation 17
4.6 Density-Matched Random-Grid Comparison 17
4.7 Sensitivity to Harmonic Construction 18
4.8 Comprehensive Harmonic Proximity Results 19
5. Discussion 19
5.1 Exploratory Identification of a Candidate Temporal Pattern 19
5.2 Methodological Contribution 21
5.3 Interpretive Framework: Constraint-Based Temporal Organization 22
5.4 Analogical Parallels in Complex Systems and Biology 23
5.5 Limitations and Future Directions 24
6. Conclusion 26
Appendix A: Fibonacci-Based Temporal Mappings (Direct and Cumulative) 27
References 30

1. Introduction

1.1 Synchronicity and the Problem of Temporal Structure

Synchronicity, originally proposed by Carl Jung, refers to the experience of meaningful coincidence between inner and outer events that are not understood as causally related (Jung, 1952). Although the construct remains theoretically controversial and difficult to operationalize, synchronicity experiences have continued to receive empirical attention in psychological and clinical research. Survey research has examined how therapists encounter and interpret synchronicity experiences in clinical settings. For example, Roxburgh et al. (2016) surveyed counsellors, psychologists, and psychotherapists regarding psychologically meaningful connections between internal experiences and external events, demonstrating that such experiences can be investigated systematically as reported psychological phenomena rather than solely through individual case descriptions.

Other empirical approaches have examined meaningful coincidences in relation to broader psychological characteristics and everyday experience. Recent research has reported associations between the experience of meaningful coincidences and creative activity and achievement, while daily-diary findings indicate that perceived meaningful coincidences fluctuate over time and are associated with affective experience (Rominger et al., 2024). Related work has also developed and validated a multidimensional measure of synchronicity awareness and meaning detection, linking individual differences in synchronicity-related experiences with meaning-making and well-being (Russo-Netzer & Icekson, 2023). Collectively, these studies demonstrate increasing efforts to operationalize and quantitatively investigate synchronicity-related experiences while also underscoring that the construct remains dependent on subjective identification and meaning attribution.

Despite these developments, comparatively little attention has been directed toward the temporal distribution of reported synchronicity events themselves. Synchronicity is inherently temporal insofar as perceived meaning depends partly on the temporal correspondence of experiences or events, yet most empirical research has focused on phenomenology, interpretation, psychological correlates, or frequency of occurrence rather than asking whether reported events exhibit measurable structure across longer periods of the lifespan. The present study addresses this narrower question. It does not attempt to establish the objective existence or causal mechanism of synchronicity; rather, it asks whether participant-identified synchronicity events exhibit nonuniform temporal clustering under a predefined mathematical framework.

1.2 Fibonacci-Based Models of Temporal Organization

One approach to modeling temporal structure in complex systems involves Fibonacci sequences and related harmonic relationships. Fibonacci numbers and associated scaling relationships have been observed in some natural growth and organizational processes, particularly in contexts involving branching, phyllotaxis, and recursive structure (Livio, 2002; West et al., 1997). Ratios related to the Fibonacci sequence and golden ratio have also been investigated in oscillatory and coordination processes in physical and biological systems (Pletzer et al., 2010).

More directly relevant to the present focus on time, Verrelli and colleagues have investigated Fibonacci-related temporal organization within cyclic human movements. Generalized finite-length Fibonacci sequences have been used to characterize relationships among phases of human gait, including features such as recursivity, asymmetry, self-similarity, and variability (Verrelli et al., 2021). Subsequent work extended this general approach to other cyclic movements, and recent theoretical synthesis has examined Fibonacci-derived temporal relationships across walking and tennis movements (Verrelli et al., 2025). These studies provide empirical and methodological examples of recursive numerical relationships being investigated in the temporal organization of biological behavior, rather than exclusively in spatial morphology.

However, an important distinction in scale and organization must be maintained. In cyclic human movement, Fibonacci-related relationships concern the durations and temporal organization of phases within an ongoing behavioral sequence, generally occurring over seconds or similarly short timescales. The present study instead examines temporal distances between an individual's birth and reported psychological events occurring years or decades later. Such lifespan-scale events are also potentially influenced by numerous biological, psychological, social, and environmental factors not represented in the harmonic model. The movement literature therefore provides an analogical precedent for investigating structured temporal organization, not direct evidence that the same mathematical organization or biological mechanism extends to lifespan-scale psychological events. Whether Fibonacci-derived relationships generalize across these substantially different temporal and organizational scales remains an empirical question.

Building on the broader possibility of structured temporal organization, previous work introduced the Fibonacci Life Chart Method (FLCM) as an exploratory framework for modeling the timing of reported synchronicity events (Sacco, 2018). Within this framework, two related models were developed: a golden section model (GSM) based on recursive interval division and a harmonic model (HM) based on periodic temporal lattice structures (Sacco, 2018). Both models generate temporal

predictions from an initial reference point, typically an individual's birth date, producing sets of temporal locations that can be compared with reported synchronicity events.

In a prior empirical study, these models were evaluated using calendar-date matching between predicted harmonic intervals and reported synchronicity events (Sacco, 2019). The harmonic model, but not the golden section model, produced a higher-than-expected frequency of matches within a ±34-day window. This preliminary finding motivated further investigation of whether the apparent correspondence represented broad temporal coverage or more localized clustering. Because the earlier analysis was exploratory and involved relatively broad temporal windows, however, it did not establish that Fibonacci-derived structure was uniquely responsible for the observed pattern.

1.3 Limitations of Calendar-Based Matching Approaches

Although the earlier findings motivated further investigation, the analytical framework employed in that study had several limitations. First, calendar-date matching required individualized simulations for each participant and did not directly isolate the intrinsic structure of the harmonic intervals. Second, reliance on binary match criteria—whether an event occurred inside or outside a specified window—discarded information concerning exact temporal proximity. Third, broad temporal windows such as ±34 days increased the proportion of the temporal domain classified as a match, making it difficult to distinguish localized clustering from correspondence produced by extensive temporal coverage.

More generally, when predicted temporal points densely populate the time axis, the probability that an observed event falls near at least one predicted point increases even under random conditions. Any evaluation of harmonic clustering therefore requires explicit control for the amount of temporal space covered by the model. This motivates an approach that evaluates exact event-to-lattice distances while accounting for lattice density and comparing observed clustering with appropriate null expectations.

1.4 Present Study: A Refined Proximity-Based Framework

The present study introduces a revised analytical framework for examining this question. Rather than evaluating reported synchronicity events exclusively in calendar time, both event timing and harmonic predictions are expressed in age-based coordinates, allowing comparison within a common continuous temporal frame. The harmonic lattice is treated as a mathematically defined temporal template against which the distribution of reported events can be evaluated. The

analysis is explicitly exploratory and probabilistic rather than deterministic and does not assume that Fibonacci-derived temporal structure constitutes an established property of synchronicity.

The framework replaces binary calendar-date matching with continuous temporal proximity, defined as the distance between each reported event and the nearest harmonic lattice point. Expected match frequencies are derived from the proportion of the observed age range covered by the lattice within a specified temporal window, explicitly accounting for differences in lattice density. The analysis is additionally restricted to primary harmonic points to reduce redundancy and near-continuous temporal coverage.

The harmonic model is then decomposed into distinct components to determine whether any observed correspondence is distributed broadly across harmonic intervals or localized to particular scales. Numerical precision and model construction are also examined by using full-precision harmonic values and comparing cumulative and direct Fibonacci-derived mappings. These comparisons are intended to evaluate the sensitivity of candidate patterns to model specification rather than to assume in advance that one Fibonacci construction is privileged.

1.5 Objectives and Hypotheses

The primary objective of the present study is to determine whether reported synchronicity events exhibit localized temporal clustering near modeled harmonic intervals when temporal coverage and resolution are explicitly considered. Specifically, the study aims to:

1. assess whether previously observed broad synchronization patterns persist under a continuous age-based framework;
2. determine whether reported events exhibit localized clustering within narrower temporal windows; and
3. determine whether any candidate clustering is distributed across harmonic intervals or localized to particular harmonic scales.

Because the present analyses evaluate multiple harmonic intervals and temporal windows without a single preregistered primary configuration, these objectives are treated as exploratory rather than confirmatory. Any localized pattern identified in the present dataset is therefore considered a candidate hypothesis requiring independent preregistered replication rather than evidence establishing Fibonacci-derived temporal organization.

1.6 Conceptual Significance

The present approach is intended primarily as a methodological framework for testing whether reported psychological events exhibit measurable temporal structure relative to predefined mathematical models. It does not assume that synchronicity events are generated by Fibonacci processes, nor does it infer a biological mechanism from analogous patterns observed at other temporal scales. Instead, it provides a quantitative means of asking whether an observed temporal distribution departs from specified null expectations and whether any such departure is selective with respect to temporal scale and model construction.

More broadly, this approach complements efforts to move the study of synchronicity and meaningful coincidence toward systematic and empirically testable investigation (Beitman, 2022). Its principal contribution is therefore not to establish a Fibonacci-based theory of synchronicity, but to provide a framework through which specific temporal hypotheses can be generated, compared, and ultimately subjected to prospective independent testing.

2. Methods

2.1 Participants and Data

The present analysis utilized data from a prior survey study of Jungian Analysts affiliated with the International Association for Analytical Psychology (IAAP). The original study was conducted between February 1 and March 1, 2018, using email invitations distributed through publicly available therapist directories.

Participants were trained Jungian Analysts with expertise in areas such as unconscious processes, dream interpretation, and synchronicity. Among the 18 respondents, the majority were female (83%), White/Caucasian/European (89%), and identified as spiritual but not religious (56%). Participants ranged in age from 32 to 72 years (M = 58.90, SD = 9.31, Median = 61.3).

Synchronicity was defined in the survey using a standard definition employed in prior research (Roxburgh et al., 2016) as “a psychologically meaningful connection between an inner event (such as a thought, vision or feeling) and one or more external events occurring simultaneously” (p. 44). To familiarize participants with the concept, Jung’s classic example of the golden scarab in the therapeutic setting was provided. Participants were instructed to report only events for which they could recall the exact date of occurrence.

For the purposes of the present analysis, synchronicity was therefore operationalized as a participant-identified event satisfying the definition supplied in

the original survey and for which an exact calendar date could be recalled. The study did not independently adjudicate whether reported events constituted synchronicities, nor was a validated diagnostic instrument used to classify events. Accordingly, the unit analyzed here is more precisely understood as a reported synchronicity event rather than an objectively verified event category.

Participants reported a total of 41 synchronicity events. Each event included the participant's age at the time of occurrence, a meaningfulness rating (1–10), and associated emotional responses. For the present analysis, synchronicity events (N = 41) were treated as the primary unit of analysis, with age at occurrence serving as the main temporal variable. The mean age at the time of synchronicity was 52.37 years. Multiple events reported by the same participant were treated as separate observations; however, a sensitivity analysis restricting the dataset to one event per participant (retaining the closest event to the harmonic lattice) yielded comparable results.

A notable concentration of reports occurred at age 49, accounting for 19.5% of all events (Figure 1). In terms of subjective significance, 56% of events were rated as highly meaningful (10/10). The most frequently reported emotions were surprise and trust (63.42% of responses).

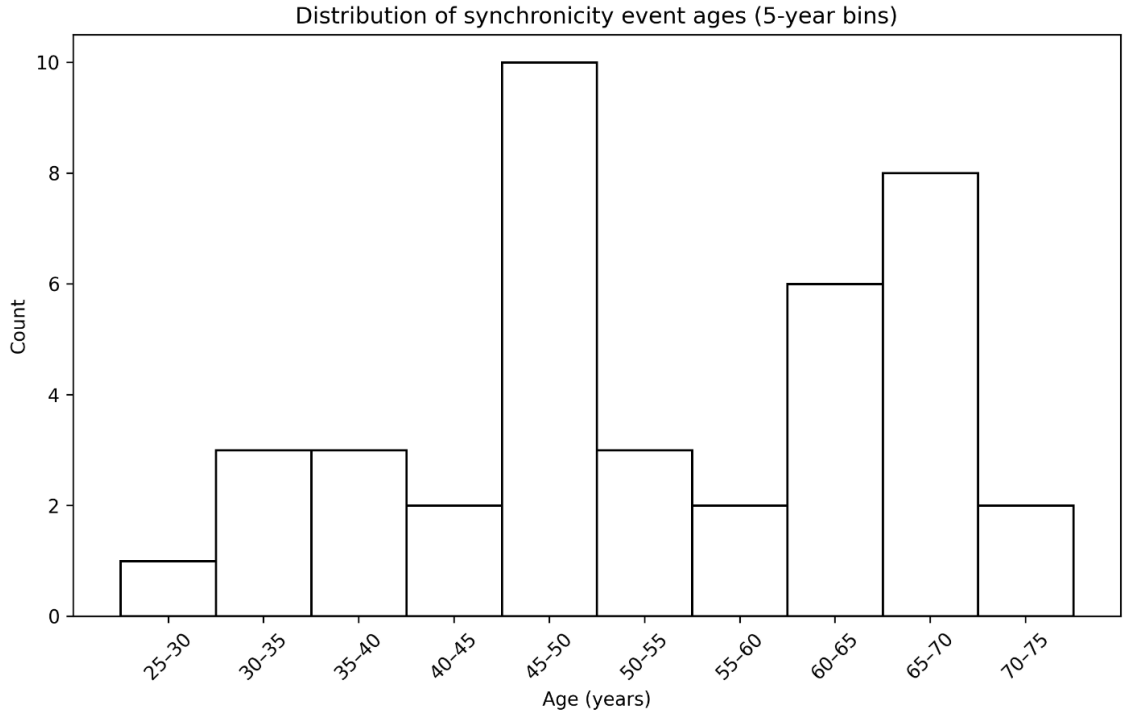


Figure 1. Distribution of synchronicity event ages. Observed event ages (N = 41) are shown as counts within 5-year bins spanning the observed age range. Events are concentrated in mid- to later-life (approximately 40–70 years), with relatively few

observations at younger ages. Binning is used for visualization only; all statistical analyses were conducted in continuous age space.

2.2 Harmonic Lattice Construction

A harmonic lattice was constructed using Fibonacci-derived intervals spanning multiple temporal scales (Table 1). Fibonacci sequences are widely observed in natural systems and are associated with recursive growth and scaling dynamics (Livio, 2002; West et al., 1997).

Each harmonic interval generates a repeating sequence of temporal points across the lifespan. For the present analysis, harmonic lattices were constructed separately for selected intervals.

Because very small harmonics produce near-continuous temporal coverage due to dense recurrence, the analysis was restricted to a subset of mid-range harmonics (0.63, 1.03, 1.67, 2.70, and 4.37 years), which provide sufficient spacing to allow meaningful discrimination between observed and expected event proximity.

Table 1

Fibonacci-Derived Harmonic Intervals Used in the Present Analysis (in Years)

Index	Harmonic Interval (years)	Scale Classification
1	0.0027	Micro-scale
2	0.0054	Micro-scale
3	0.0109	Micro-scale
4	0.0192	Micro-scale
5	0.0329	Micro-scale
6	0.0548	Micro-scale
7	0.0904	Micro-scale
8	0.1479	Micro-scale
9	0.2411	Micro-scale
10	0.3918	Micro-scale
11	0.6356	Lower mid-scale
12	1.0301	Mid-scale
13	1.6685	Mid-scale
14	2.7013	Mid-scale
15	4.3726	Upper mid-scale
16	7.0767	Macro-scale
17	11.4521	Macro-scale

Index	Harmonic Interval (years)	Scale Classification
18	18.5315	Macro-scale
19	29.9863	Macro-scale
20	48.5205	Macro-scale
21	78.5096	Macro-scale

2.3 Distance-to-Lattice Calculation

For each synchronicity event, the temporal distance to the nearest harmonic lattice point was computed:

$$d_i = \min_{l \in L} |a_i - l|$$

Where represents the age of the event and the set of harmonic lattice points.

2.4 Window Definition

Proximity windows of ±3, ±5, and ±10 days were tested. These were converted to years:

- ±3 days = $3/365$
- ±5 days = $5/365$
- ±10 days = $10/365$

An event was classified as a “hit” if its nearest distance fell within the specified window.

2.5 Coverage-Based Expected Values

Expected hit frequencies were calculated based on the proportion of the age range covered by the lattice within each window. This approach is conceptually related to coverage-based probability estimation in continuous spaces (Silverman, 1986).

A dense grid of ages spanning the observed range was generated, and for each grid point the distance to the nearest lattice point was computed. Coverage was defined as the proportion of grid points falling within the specified window.

Expected hits were then calculated as:

$$E = p \times N$$

where is coverage and .

2.6 Statistical Analysis

Observed and expected hit frequencies were compared using a chi-square goodness-of-fit test (Pearson, 1900).

$$\chi^2 = \frac{(O_{\text{hit}} - E)^2}{E} + \frac{\left(O_{\text{miss}} - (N - E)\right)^2}{N - E}$$

Significance was evaluated at .

2.7 Precision and Numerical Specification of Harmonic Intervals

Harmonic intervals were defined using full-precision values derived from the Fibonacci sequence (e.g., 1.668493151 years) to preserve the exact temporal structure of the lattice and avoid systematic distortion introduced by rounding. Although rounded approximations (e.g., 1.67 years) differ only slightly at the level of a single interval (~0.0027 years, or ~1 day), this discrepancy accumulates across successive multiples, producing shifts on the order of several weeks at later ages and potentially affecting classification of events within narrow proximity windows. Accordingly, all primary analyses were conducted using full-precision values. At the level of precision employed (9–10 decimal places), residual numerical error is on the order of seconds across the lifespan and is therefore negligible relative to the temporal resolution of the analysis (±3 to ±10 days), effectively eliminating cumulative distortion.

2.8 Permutation Testing

To validate results independently of parametric assumptions, a permutation test was conducted. Permutation testing provides a nonparametric approach for estimating empirical null distributions (Good, 2005). Event ages were randomly sampled from a uniform distribution spanning the observed age range (), and the number of events falling within each proximity window was recomputed. This procedure was repeated 50,000 times to generate an empirical null distribution of hit counts. The permutation p-value was defined as the proportion of simulations producing equal or greater hit counts than observed.

As a robustness check, an additional age-distribution-matched permutation test was conducted in which simulated event ages were sampled from the empirical age distribution of the observed data. This alternative null model preserves the non-uniform age structure of the sample while maintaining identical proximity criteria.

2.9 Density-Matched Random-Grid Analysis

To evaluate whether the observed clustering could arise simply because any temporal grid of comparable density would produce similar proximity matches, an additional density-matched random-grid analysis was conducted. The observed 41 event ages were held fixed while 1,000,000 random temporal grids were generated across the observed age range (23.236–72.444 years). Each simulated grid contained 30 temporal points, matching the number of 1.668493151-year cumulative lattice positions within this range. For each simulated grid, the number of observed events occurring within ±5 days of a grid point was calculated. The empirical probability was defined as the proportion of random grids producing three or more matches, corresponding to the number observed for the Fibonacci-derived lattice. As sensitivity analyses, the procedure was repeated using stratified random grids and randomly phase-shifted regular grids.

2.10 Direct vs. Cumulative Harmonic Construction

Harmonic intervals were derived using both cumulative and direct Fibonacci mappings. In the cumulative mapping, temporal values correspond to the accumulated sum of preceding Fibonacci numbers, whereas in the direct mapping each interval corresponds to a single Fibonacci value scaled to years. Although these mappings produce closely related values, small differences accumulate across multiples, potentially altering lattice alignment. Both constructions were evaluated to determine whether observed clustering reflects general Fibonacci scaling or depends on specific temporal formulations.

2.11 Harmonic-Specific Analysis

Each harmonic interval was tested independently using identical procedures to determine whether proximity effects were uniformly distributed or selectively associated with specific harmonic scales.

2.12 Multiple Comparisons and Exploratory Inference

Five harmonic intervals were evaluated across three proximity windows, yielding 15 harmonic-by-window comparisons. Because these analyses were exploratory rather than based on a single prespecified primary harmonic and window, nominal p-values were used to characterize candidate patterns rather than establish confirmatory significance. To account for multiple comparisons, a Bonferroni adjustment was applied across the 15 harmonic-by-window comparisons, corresponding to an adjusted significance threshold of $\alpha = .0033$. Effects not

surviving this adjustment were treated as hypothesis-generating and requiring independent preregistered confirmation.

2.13 AI-Assisted Analysis

Portions of the statistical analysis and data processing were implemented with the assistance of an AI-based language model (ChatGPT, OpenAI, GPT-5.3). The model was used to support code generation, verification of analytical procedures, and reproducibility checks under the direction of the author. All analytical decisions, model specifications, and final interpretations were determined by the author.

3. Methodological Comparison with Prior Study

The present study employs a revised analytical framework that differs in several key respects from the original investigation reported in Sacco (2019). These differences reflect a progression from calendar-based matching toward a more precise analysis of temporal proximity within harmonic structures.

3.1 Time Representation

The prior study evaluated synchronicity events in calendar time, generating harmonic model (HM) and golden section model (GSM) predictions as calendar dates derived from each participant's birthdate. Observed synchronicity dates were compared directly to these predicted dates.

In the present study, both synchronicity events and harmonic attractors are expressed in age-based coordinates. This transformation removes dependence on individual birthdates and allows evaluation against a common harmonic lattice, thereby isolating the intrinsic temporal structure of the model.

3.2 Personalization vs. Universal Lattice

The 2019 study implemented individualized lifechart simulations, producing participant-specific sets of predicted dates.

In contrast, the present study utilizes a universal harmonic lattice, reflecting the invariant structure of harmonic intervals. Because harmonic ages are translation-invariant with respect to birthdate, this approach permits aggregation across participants and direct comparison of event proximity to shared attractor locations.

3.3 Matching Criterion

In the prior study, synchronicity events were evaluated using a binary match criterion, in which an event was classified as a match if at least one predicted harmonic date fell within a predefined window.

The present study replaces this approach with a continuous proximity measure, defined as the temporal distance between each event and the nearest harmonic lattice point. This allows more precise quantification of alignment and avoids information loss associated with dichotomization. The proximity calculation and harmonic-lattice construction are illustrated schematically in Figure 2A.

3.4 Window Structure

The original analysis employed broad temporal windows derived from Fibonacci intervals (±13, ±21, ±34, ±55, and ±89 days).

The present study instead evaluates narrow, high-resolution windows (±3, ±5, and ±10 days), enabling detection of localized clustering effects that may be obscured at larger scales.

3.5 Lattice Composition

The 2019 HM algorithm generated a dense set of predicted dates, including both primary harmonic intervals and derived points, resulting in high temporal coverage.

The present study restricts analysis to primary harmonic points only, reducing lattice density and preserving statistical contrast between regions that are near versus not near harmonic attractors.

3.6 Statistical Baseline

Both studies account for expected match frequencies based on temporal coverage. The prior study estimated expected values based on the proportion of calendar days within each window.

The present study extends this approach by computing continuous coverage of the age space under each harmonic lattice and window, providing a more precise control for density effects under high-resolution conditions.

3.7 Harmonic Structure

The original analysis evaluated harmonic predictions as a unified model.

The present study decomposes the harmonic lattice into distinct harmonic components (e.g., 0.63, 1.03, 1.67, 2.70, and 4.37 years), allowing assessment of

whether effects are uniformly distributed or selectively associated with specific harmonic scales.

3.8 Conceptual Shift

Taken together, these methodological changes reflect a shift from evaluating whether events occur within broad temporal windows of predicted harmonic dates to testing whether events exhibit statistically significant clustering in proximity to specific harmonic attractors under controlled conditions.

The present approach should therefore be understood as a refinement rather than a reanalysis of prior findings. While the earlier study identified a broad synchronization range, the current framework enables detection of finer-scale structure, including narrow proximity effects and harmonic-specific selectivity.

Key methodological differences between the prior and present studies are summarized in Table 2.

Table 2. Key methodological differences between prior and present study

Feature	2019 Study	New Study
Time variable	Calendar date	Age
Personalization	Yes (birthdate)	No
Matching	Binary (hit/no hit)	Continuous distance
Windows	Large (13–89 days)	Small (3–10 days)
Density control	Partial	Explicit
Midpoints	Included	Removed
Harmonics	Pooled	Separated

3.9 Additional Validation Procedures

The present study further extends prior methodology through nonparametric permutation testing and comparison of cumulative versus direct harmonic constructions. These analyses assess whether candidate clustering is robust to distributional assumptions and temporal representation.

4. Results

4.1 Relationship to Prior Broad-Window Findings

Previous work (Sacco, 2019) reported that synchronicity events occurred more frequently than expected by chance within a ±34-day window of harmonic model (HM) predictions using a calendar-based matching approach. This finding suggested

the presence of a broad temporal synchronization range associated with harmonic intervals.

The present study does not directly replicate this analysis, as it employs a different methodological framework based on age-normalized coordinates, continuous proximity measures, and restriction to primary harmonic points. As such, the earlier ±34-day result is referenced here as a prior empirical observation rather than as a replicated finding within the current design.

The earlier ±34-day finding is treated here as a coarse prior observation; the present analysis instead tests for finer-scale structure using narrower windows, harmonic-specific effects, and explicit control for lattice density.

4.2 Emergence of a Candidate Narrow-Band Pattern Under High-Resolution Analysis

When the analysis was restricted to primary harmonic points and evaluated across ±3-, ±5-, and ±10-day windows, the strongest nominal deviation from expected coverage occurred for the 1.668493151-year cumulative harmonic within the ±5-day window. No comparable nominal effect was observed at the ±3- or ±10-day windows or across the remaining harmonic intervals. Because this pattern emerged from 15 exploratory harmonic-by-window comparisons and did not survive adjustment for multiple comparisons, it is interpreted as a localized candidate signal rather than evidence of confirmed harmonic alignment. The pattern nevertheless identifies a specific temporal scale and proximity window for prospective testing in an independent dataset.

4.3 Harmonic Component Decomposition and Robustness

Analysis of individual harmonic components indicated that the strongest nominal clustering was localized to the 1.668493151-year harmonic, with a weaker secondary pattern near the 2.701369863-year harmonic (Table 3).

Within the ±5-day window, three events occurred near the 1.668493151-year harmonic compared with approximately 0.68 expected under the null model. The exact binomial test yielded a nominal probability of $p = .031$, closely matched by permutation testing ($p = .031$); the corresponding chi-square statistic was $\chi^2(1) = 8.11$, $p = .004$. However, the exact result did not survive Bonferroni adjustment across the 15 harmonic-by-window comparisons (adjusted $p = .464$) and is therefore interpreted as an exploratory candidate signal rather than confirmatory statistical evidence.

The 2.701369863-year harmonic also produced an elevated chi-square statistic, $\chi^2(1) = 6.04$, $p = .014$, but the corresponding exact test was non-significant ($p = .066$). This pattern was therefore treated as a weaker secondary observation rather than evidence of harmonic clustering. No comparable nominal patterns were observed for the remaining harmonic intervals within the ±5-day window.

Table 3
Exploratory harmonic clustering results within the ±5-day window

Harmonic Interval (years)	Window	χ^2	p-value	Exact p	Permutation p	Significance Summary
1.668493151	±5 days	8.11	0.0044	0.031	0.031	Nominal exploratory signal
2.701369863	±5 days	6.04	0.0139	0.066	—	Secondary nominal pattern; exact test non-significant
Other harmonics	—	—	—	—	—	No significant effects

Note. *p*-values shown in the table are unadjusted. The exact $p = .031$ for the 1.668493151-year/±5-day configuration did not survive Bonferroni adjustment across the 15 harmonic-by-window comparisons (adjusted $p = .464$; adjusted $\alpha = .0033$).

4.4 Localized Harmonic Alignment

The nominal clustering signal at the 1.668493151-year harmonic was driven by a small number of high-proximity events rather than diffuse alignment across the lattice. Within the ±5-day window, 3 events were observed compared with approximately 0.68 expected under the null model. These events occurred within 1.7 to 4.7 days of the nearest harmonic lattice point.

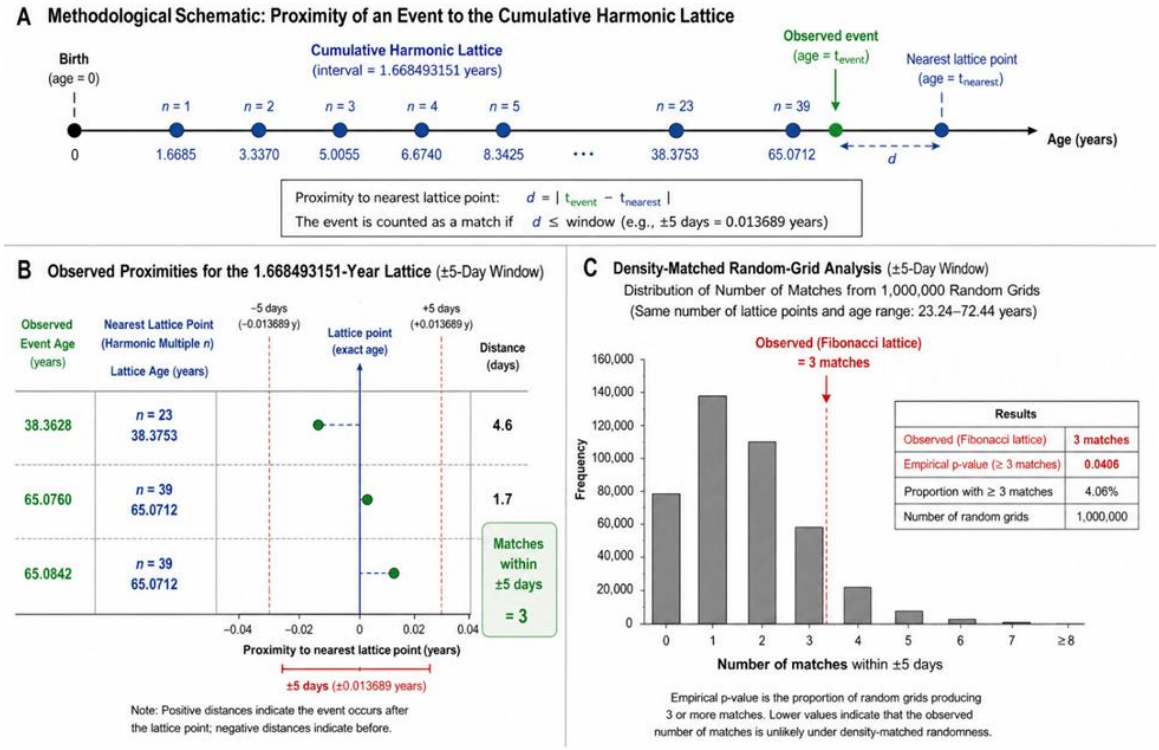
These events corresponded to harmonic multiples (n = 23 and n = 39), suggesting that clustering is localized within specific regions of the harmonic lattice rather than uniformly distributed across all multiples. Notably, two events occurred at the same harmonic multiple (n = 39) and were reported by the same participant, indicating repeated alignment near a single lattice position rather than independent matches across distinct regions. This pattern does not account for the overall effect, which remains significant under a one-event-per-participant constraint.

The corresponding harmonic lattice positions are: n = 23 → 38.3753 years and n = 39 → 65.0712 years, with one event occurring near the n = 23 position and two events near the n = 39 position, all within 1.7–4.7 days of these values.

Table 4. Observed events and corresponding harmonic lattice positions

Observed Age	Harmonic Multiple (n)	Harmonic Age	Distance (days)
65.0760	39	65.0712	1.7
38.3628	23	38.3753	4.6
65.0842	39	65.0712	4.7

The corresponding harmonic lattice positions were n = 23 → 38.3753 years and n = 39 → 65.0712 years, with observed events occurring within 1.7–4.7 days of these values (Table 4; Figure 2B). The proximity procedure used to identify these events is illustrated in Figure 2A.



(A) Schematic illustration of the proximity-based method. Event age is compared with the cumulative 1.668493151-year harmonic lattice, and proximity (*d*) is defined as the absolute temporal distance between an observed event and the nearest lattice point. Events occurring within ±5 days (±0.01369 years) of a lattice point are classified as matches for the corresponding analysis. **(B)** The three observed events meeting the ±5-day criterion for the cumulative 1.668493151-year lattice. One event at age 38.3628 occurred 4.6 days from the n = 23 lattice point (38.3753 years), while two events from the same participant, at ages 65.0760 and 65.0842, occurred 1.7 and 4.7 days from the n = 39 lattice point (65.0712 years), respectively. **(C)** Density-matched random-grid comparison. The 41 observed event ages were held fixed while 1,000,000 random temporal grids containing the same

number of lattice points across the same observed age range as the cumulative 1.668493151-year lattice were generated. The Fibonacci-derived lattice produced three ±5-day matches; 4.06% of density-matched random grids produced three or more matches (empirical p = .0406). Because the 1.668493151-year/±5-day configuration was identified within the broader exploratory analysis, this random-grid comparison is interpreted as a supplementary robustness analysis rather than independent confirmatory evidence.

As an additional robustness check, the analysis was repeated under a one-event-per-participant constraint, retaining only the closest event to the 1.668493151 harmonic for each respondent. Under this restriction, 2 matches were observed among 18 participants, compared with 0.30 expected under the null model, and the effect remained significant (exact p = .035).

4.5 Permutation Validation

For the selected 1.668493151-year/±5-day combination, 50,000 simulations yielded a nominal permutation probability of p = .031, closely matching the exact binomial result (p = .031). This convergence indicates that the nominal probability estimate for this particular configuration is not dependent on the parametric test employed. However, because the configuration emerged from the broader harmonic-by-window analysis, these individual-test probabilities should not be interpreted as confirmatory evidence independent of the multiple-comparison issue.

As a robustness check, an age-distribution-matched permutation test was conducted in which simulated event ages were drawn from the empirical age profile rather than from a uniform range. Results closely replicated those obtained under the uniform null, with the 1.668493151 harmonic remaining significant (p = .031), indicating that the observed clustering is not attributable to age-density effects.

Although only three matches were observed, the expected number under the null model is low (approximately 0.68 events) due to the limited temporal coverage of the ±5-day window, and thus the observed count represents a substantial deviation from chance.

4.6 Density-Matched Random-Grid Comparison

The cumulative 1.668493151-year lattice produced three observed matches within ±5 days. Among 1,000,000 density-matched random grids containing the same number of temporal points across the observed age range, 40,551 produced three or more matches (p = .0406). As shown in Figure 2C, the observed count of three matches exceeded that obtained for approximately 96% of density-matched

random temporal grids. Comparable results were obtained using stratified random grids (p = .0402) and randomly phase-shifted regular grids preserving the 1.668493151-year spacing (p = .0278). Because the 1.668493151-year/±5-day configuration was identified within the broader exploratory harmonic-by-window analysis, these random-grid comparisons are interpreted as supplementary robustness tests rather than independent confirmatory evidence.

4.7 Sensitivity to Harmonic Construction

A sensitivity analysis compared cumulative and direct implementations of the 1.668493151-year harmonic (see Appendix). Under the cumulative construction, three events occurred within the ±5-day window, producing the strongest nominal signal observed in the harmonic-by-window analysis (exact p = .031; permutation p = .031). Under the direct construction, no events occurred within the same window (Table 5). Although the difference between mappings is small at the level of a single interval (~1 day), this discrepancy accumulates across successive multiples, producing shifts on the order of weeks at later ages. This contrast demonstrates that the candidate pattern is sensitive to the precise temporal construction of the lattice. Although the cumulative and direct mappings are both mathematically defined from Fibonacci-derived intervals, the present data cannot establish that the cumulative construction is uniquely or biologically privileged. Rather, the disappearance of the pattern under a small change in temporal construction increases the need for independent prospective testing of the cumulative specification.

Table 5
Comparison of cumulative and direct mapping (±5 days)

Mapping	Harmonic	Matches	Exact p
Cumulative	1.668493151	3	.031
Direct	1.671232877	0	1.00

Importantly, the cumulative and direct mappings were mathematically specified from the Fibonacci-derived construction rather than obtained by continuously adjusting lattice parameters to maximize correspondence with the observed events. Thus, the cumulative 1.668493151-year interval was not numerically fitted to the three high-proximity observations. Nevertheless, because multiple harmonic intervals, temporal windows, and mapping constructions were examined within the broader exploratory analysis, the apparent advantage of the cumulative specification may reflect model selection within this dataset and therefore requires independent confirmation.

4.8 Comprehensive Harmonic Proximity Results

Full harmonic-specific results across all tested window sizes under the cumulative harmonic mapping are presented in Table 6.

Table 6

Full harmonic proximity results across windows (±3, ±5, ±10 days) under the cumulative harmonic mapping

Harmonic Interval (years)	Window	Hits	Expected	Coverage	χ^2 p-value	Exact p-value
0.635616438	±3 days	0	1.062	0.0259	0.2964	1.0000
0.635616438	±5 days	2	1.763	0.0430	0.8552	0.5311
0.635616438	±10 days	3	3.534	0.0862	0.7663	0.6980
1.030136986	±3 days	0	0.656	0.0160	0.4142	1.0000
1.030136986	±5 days	0	1.087	0.0265	0.2908	1.0000
1.030136986	±10 days	2	2.198	0.0536	0.8910	0.6529
1.668493151	±3 days	1	0.406	0.0099	0.3487	0.3350
1.668493151	±5 days	3	0.676	0.0165	0.0044	0.0310
1.668493151	±10 days	3	1.365	0.0333	0.1548	0.1556
2.701369863	±3 days	0	0.258	0.0063	0.6102	1.0000
2.701369863	±5 days	2	0.418	0.0102	0.0139	0.0657
2.701369863	±10 days	2	0.824	0.0201	0.1907	0.1992
4.372602740	±3 days	0	0.156	0.0038	0.6925	1.0000
4.372602740	±5 days	0	0.250	0.0061	0.6159	1.0000
4.372602740	±10 days	0	0.504	0.0123	0.4749	1.0000

Note. Values are unadjusted exploratory statistics across 15 harmonic-by-window comparisons. The nominal exact effect at 1.668493151 years/±5 days ($p = .031$) did not survive Bonferroni adjustment across the 15 comparisons (adjusted $p = .464$; adjusted $\alpha = .0033$) and is therefore interpreted as hypothesis-generating.

5. Discussion

5.1 Exploratory Identification of a Candidate Temporal Pattern

The principal contribution of the present study is methodological. Relative to earlier calendar-based matching, the framework uses age-based coordinates,

continuous nearest-lattice proximity, coverage-based expected values, and separate harmonic intervals. Together, these refinements improve temporal resolution and reduce density-related inflation while allowing localized clustering to be tested within a shared age-based temporal framework (Mitchell, 2009; Sacco, 2019).

By estimating expected hit frequencies directly from lattice coverage, the analysis preserves statistical contrast between regions near and far from modeled harmonic positions. These procedures do not eliminate analytic flexibility or multiple-comparison concerns, but they provide a more constrained and transparent basis for testing temporal clustering.

The framework is probabilistic rather than deterministic or mechanistic: it tests whether event likelihood varies relative to predefined temporal templates rather than predicting individual events or exact triggering times.

The present exploratory analysis identified a localized candidate clustering pattern near the cumulative 1.668493151-year harmonic within a ±5-day window. Three events occurred within this interval compared with approximately 0.68 expected under the corresponding null model, yielding nominal exact and permutation probabilities of $p = .031$. However, this pattern emerged from a broader analysis involving five harmonic intervals and three temporal windows and did not survive Bonferroni adjustment for these 15 comparisons (adjusted $p = .464$).

The principal empirical contribution of this analysis is consequently not the establishment of a temporal harmonic effect, but the reduction of a broad hypothesis into a substantially more specific and falsifiable prediction. The exploratory results identify the cumulative 1.668493151-year lattice within a ±5-day proximity window as a candidate configuration for prospective testing. An independent replication can therefore evaluate this configuration as a single preregistered primary hypothesis, without selecting the harmonic interval or temporal window after examination of the replication data.

The present results remain preliminary and hypothesis-generating rather than confirmatory. The primary effect was driven by a small number of high-proximity events within a modest retrospective sample. Although exact and permutation tests converged on similar probability estimates, the findings should be interpreted cautiously given the exploratory nature of the analysis, the number of harmonic-window comparisons examined, and the absence of preregistered model specification. The present findings therefore do not establish a generalized temporal law or formal dynamical attractor system in the technical sense used in nonlinear dynamics (Kelso, 1995). Rather, it introduces an exploratory framework for investigating whether reported meaningful coincidences exhibit structured

deviations from uniform temporal distributions under predefined temporal templates.

The cumulative-versus-direct comparison further demonstrates that the candidate pattern is sensitive to model specification. The nominal clustering observed under the cumulative 1.668493151-year construction was absent under the corresponding direct mapping. Although this contrast is consistent with the cumulative construction used in the present framework, it does not establish that cumulative Fibonacci organization is uniquely privileged. Given the exploratory evaluation of alternative analytical configurations, the difference may reflect either genuine model specificity or chance model selection within the present dataset. Distinguishing between these possibilities requires prospective testing in which the cumulative 1.668493151-year construction and ±5-day window are specified before examination of an independent sample.

5.2 Methodological Contribution

The principal contribution of the present study is methodological rather than ontological. Relative to earlier calendar-based matching approaches, the present framework introduces several refinements designed to improve temporal resolution and reduce density-related inflation effects. These include: (i) transformation of synchronicity events into age-based coordinates, (ii) use of continuous nearest-lattice proximity measures rather than binary hit/no-hit classification, (iii) explicit estimation of expected values from lattice coverage within continuous age space, and (iv) decomposition of harmonic structure into separate harmonic intervals rather than pooled temporal predictions.

Together, these refinements allow investigation of localized clustering effects under conditions that preserve statistical contrast between regions near versus not near modeled harmonic positions, consistent with broader approaches used in the study of structured organization within complex systems (Mitchell, 2009). In this respect, the present framework differs substantially from previous work, which relied on individualized calendar-date predictions and broad temporal windows (Sacco, 2019). Rather than evaluating whether synchronicity events simply occur within large neighborhoods of predicted dates, the current study attempts to examine whether finer-scale structure may exist within a shared age-based temporal framework.

The use of continuous proximity measures is especially important because binary matching procedures can obscure local variation and inflate apparent correspondence under dense temporal coverage. By estimating expected hit frequencies directly from lattice coverage, the present study attempts to address

this issue explicitly. While these procedures do not eliminate concerns regarding analytic flexibility or multiple comparisons, they represent a methodological step toward more constrained and transparent analyses of temporal clustering in synchronicity reports.

More broadly, the present framework should be understood as a probabilistic organizational model rather than a deterministic or mechanistic account. The analysis does not attempt to predict individual synchronicity events, nor does it propose exact triggering points in time. Instead, the model examines whether event likelihood may vary nonuniformly relative to predefined temporal templates under specified statistical conditions.

5.3 Interpretive Framework: Constraint-Based Temporal Organization

Within the present paper, "constraint" refers not to a hidden force, causal agency, or metaphysical organizing principle, but to statistical restrictions on the distribution of event times under a predefined temporal model. From this perspective, the observed clustering results can be interpreted as preliminary evidence that synchronicity reports may exhibit structured temporal organization under certain temporal constructions rather than being uniformly distributed across the lifespan.

A useful analogy is that of trajectories moving across a constrained landscape. In many complex systems, outcomes are shaped not only by local interactions but also by the broader organization of accessible pathways available to the system. The constraints do not directly determine any single event, but they may influence the distribution of possible trajectories over time. Applied cautiously, the present findings are compatible with the possibility that synchronicity reports reflect probabilistic clustering within structured temporal intervals rather than purely random temporal dispersion. Such an interpretation is broadly compatible with complex systems frameworks in which macroscopic organization emerges through constrained interactions operating under non-equilibrium conditions rather than through centralized control or direct linear causation (Nicolis & Prigogine, 1977; Kauffman, 1993; Mitchell, 2009).

Importantly, the present framework should not be interpreted as implying hidden temporal fields, acausal signaling mechanisms, or formal dynamical attractors in the strict technical sense used in nonlinear dynamics. In mathematical dynamical systems theory, attractors are rigorously defined properties of trajectories evolving within explicit state spaces under specified update rules. The current study does not implement such a formal dynamical system involving explicit state variables,

trajectories, basins of convergence, or phase-space dynamics as typically defined within dynamical systems theory (Kelso, 1995).

At the same time, the observed selective clustering may be compatible with a weaker organizational interpretation in which certain harmonic intervals function as attractor-like regions of elevated temporal probability within a probabilistic temporal framework. Under this interpretation, terms such as “harmonic attractor” are intended not as literal dynamical attractors, but as descriptive shorthand for localized regions of elevated proximity and nonuniform event clustering under the modeled temporal lattice.

Similarly, concepts such as recursive accumulation and state-dependent responsiveness should be interpreted as abstract organizational ideas rather than inferred mechanisms. Within systems biology and developmental frameworks, related concepts have been used to describe how prior system states can shape later responsiveness and trajectory selection under changing environmental conditions (Noble, 2012; Torday, 2015, 2016). The present data do not identify causal processes operating beneath synchronicity experiences. Rather, they motivate the narrower possibility that temporal organization may be history-sensitive and nonuniform under certain modeling assumptions.

Under this interpretation, the cumulative temporal mapping may be viewed as representing one possible way of modeling temporally integrated developmental structure. However, because the present findings remain exploratory, the cumulative-versus-direct distinction should presently be treated as a hypothesis-generating result requiring independent replication and comparison against alternative temporal frameworks.

5.4 Analogical Parallels in Complex Systems and Biology

The biological and complex-systems parallels below are formal analogies for history dependence, selective responsiveness, and constraint-mediated organization, not proposed mechanisms of synchronicity.

Many biological systems exhibit forms of path dependence in which prior states influence later responsiveness without rigidly determining outcomes. Examples include epigenetic regulation, developmental canalization, homeostatic adaptation, and distributed regulatory coordination in multicellular systems. In such systems, historical organization can shape future sensitivity in selective and nonuniform ways while remaining probabilistic and context dependent.

Likewise, systems-level coordination can emerge through distributed interactions operating under shared constraints rather than through centralized control. Examples such as quorum sensing, developmental regulation, and recurrent neural

dynamics demonstrate that complex organization may arise from local interactions embedded within structured regulatory conditions. More broadly, systems-oriented biological frameworks increasingly describe living organization in terms of distributed relational processes operating across multiple scales rather than strictly reductionistic causal chains (Torday & Miller, 2021). The relevance of these analogies lies not in demonstrating equivalent mechanisms for synchronicity, but in showing that concepts such as history dependence, state sensitivity, recursive organization, and constraint-mediated pattern selection are already recognized principles within complex adaptive systems.

These analogies situate the temporal model within broader organizational frameworks involving probabilistic structure, distributed regulation, and non-equilibrium dynamics; they do not imply that synchronicity is generated by epigenetic or neural mechanisms or that Fibonacci timing is biologically encoded.

Recent work on cyclic human movement provides a particularly relevant example of Fibonacci-related temporal organization. Verrelli and colleagues have identified Fibonacci- and golden-ratio-related temporal relationships in the organization of human walking, swimming, and tennis movements (Verrelli et al., 2021a, 2021b, 2024, 2025). These studies suggest that recursive numerical relationships may characterize the temporal organization of biological behavior in addition to morphological structure.

However, these findings operate at a fundamentally different temporal and organizational scale from the hypothesis examined here. In cyclic human movement, Fibonacci-related relationships are identified among phase durations within an ongoing behavioral sequence, typically over relatively short timescales. The present study instead examines temporal distances between birth and reported synchronicity events occurring across the lifespan. The movement literature therefore provides an analogical precedent for structured temporal organization rather than direct evidence for the lifespan-scale harmonic model proposed here. Whether Fibonacci-derived temporal relationships generalize across these distinct scales and forms of organization remains an empirical question.

5.5 Limitations and Future Directions

Several important limitations substantially constrain interpretation of the present findings. First, the sample size is modest and consists of retrospective reports drawn from a specialized population of Jungian analysts who are already familiar with synchronicity concepts. This raises potential concerns regarding recall bias, interpretive bias, and selective reporting of meaningful events. The observed effects

were also driven by a small number of high-proximity observations, including repeated clustering near the same harmonic multiple.

Second, the analysis examined multiple harmonic intervals, proximity windows, and temporal constructions, increasing the possibility of false-positive findings. The nominal 1.668493151-year/±5-day effect did not survive multiple-comparison adjustment and should therefore be treated as a candidate effect. Future work should preregister the cumulative 1.668493151-year harmonic, the ±5-day window, and a single primary endpoint in an independent dataset.

Third, the candidate pattern was sensitive to lattice construction: clustering under the cumulative 1.668493151-year mapping disappeared under the corresponding direct mapping. This limits claims of robustness and prevents the present data from establishing the cumulative construction as uniquely privileged. Although the lattice parameters were mathematically derived rather than fitted to the observed events, selection among alternative model specifications remains a source of analytic flexibility.

The present study does not establish Fibonacci structure as uniquely privileged relative to alternative temporal organizations. Future work should therefore compare cumulative Fibonacci lattices against explicit competitor models, including logarithmic spacing, periodic baselines, random density-matched lattices, culturally salient age anchors, and alternative scaling functions. Such comparisons will be necessary to determine whether the observed effects reflect specific properties of Fibonacci-derived temporal organization or more general forms of nonuniform event clustering.

Additional methodological refinements would further strengthen future investigations. These may include participant-level hierarchical modeling, robustness and sensitivity analyses across alternative parameter choices, preregistered window selection, alternative null distributions, longitudinal sampling designs, and independent replication in broader general populations. Future studies may also benefit from prospective event collection methods designed to reduce retrospective reconstruction and recall biases.

Finally, although the present paper adopts language drawn from complex systems and constraint-based organization, the current framework remains descriptive and exploratory rather than mechanistic. The study does not identify underlying causal processes and should not be interpreted as evidence for hidden temporal fields, deterministic prediction systems, or formal dynamical attractors. The most defensible interpretation at present is narrower: reported synchronicity events may exhibit localized deviations from uniform temporal distributions under certain predefined temporal constructions. Whether such deviations reflect meaningful

organizational structure, statistical artifact, or broader forms of temporal patterning remains an open empirical question requiring substantially larger and more rigorous investigation.

6. Conclusion

The present study developed a high-resolution framework for evaluating temporal clustering of reported synchronicity events using continuous proximity to Fibonacci-derived harmonic lattices. Exploratory analysis identified a localized candidate pattern near the cumulative 1.668493151-year harmonic within a ±5-day window, where three events were observed compared with approximately 0.68 expected under the null model. Although this pattern yielded nominally significant exact and permutation results, it did not survive adjustment for multiple comparisons and therefore cannot presently be considered confirmatory evidence of harmonic temporal organization.

The principal contribution of the finding is instead hypothesis refinement. A broad hypothesis concerning Fibonacci-derived temporal organization has been reduced to a precise prospective prediction: the cumulative 1.668493151-year lattice within a ±5-day window. Independent preregistered testing of this single primary configuration will be necessary to determine whether the observed pattern represents reproducible temporal structure or an exploratory statistical fluctuation.

Appendix A: Fibonacci-Based Temporal Mappings (Direct and Cumulative)

This appendix presents two ways of mapping the Fibonacci sequence onto temporal structure. In the direct mapping, each stage corresponds to a single Fibonacci value, treating time as a series of discrete, expanding intervals. Each stage is considered independently, emphasizing the spacing between successive phases.

In the cumulative mapping, each stage represents the sum of all preceding Fibonacci values, treating time as a continuous process of accumulation. This approach emphasizes total elapsed development rather than isolated intervals.

Both mappings use the same sequence and scale but differ in perspective: the direct mapping models time as successive intervals, while the cumulative mapping models it as ongoing developmental growth. The geometric basis of this distinction is illustrated in Figure A1.

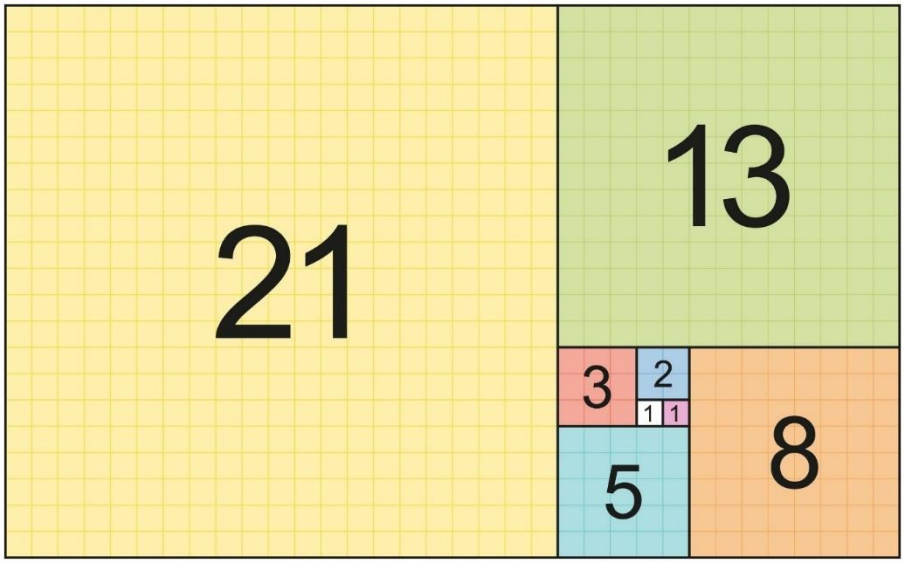


Figure A1. Geometric illustration of the Fibonacci summation identity showing that the cumulative sum of preceding terms equals the Fibonacci value two indices ahead minus one. For example, the sum of the first four terms (1 + 1 + 2 + 3 = 7) equals F6 − 1, since F6 = 8.

Table A1: Direct Fibonacci Values

Direct Fibonacci F_nFn	**Years (Direct, 10 d.p.)**
1	0
1	0
2	0.005479452
3	0.008219178
5	0.01369863
8	0.021917808
13	0.035616438
21	0.057534247
34	0.093150685
55	0.150684932
89	0.243835616
144	0.394520548
233	0.638356164
377	1.032876712
610	1.671232877
987	2.704109589
1,597	4.375342466
2,584	7.079452055
4,181	11.45479452
6,765	18.53424658
10,946	29.9890411
17,711	48.52328767
28,657	78.51232877
46,368	127.0356164

Note. Fibonacci values are presented directly, where each row corresponds to a single Fibonacci number.

Table A2: Cumulative Fibonacci Values

Cumulative Fibonacci ΣFn	**Years (Cumulative, 10 d.p.)**
1	0.002739726
2	0.005479452
4	0.010958904
7	0.019178082
12	0.032876712
20	0.054794521
33	0.090410959
54	0.147945206
88	0.24109589
143	0.391780822
232	0.635616438
376	1.030136986
609	1.668493151
986	2.701369863
1,596	4.37260274
2,583	7.076712329
4,180	11.45205479
6,764	18.53150685
10,945	29.98630137
17,710	48.52054795
28,656	78.50958904
46,367	127.030137

Note. Cumulative Fibonacci values represent the running total obtained by summing all Fibonacci numbers up to the given row.

References

Beitman, B. D. (2022). Meaningful Coincidences: How and Why Synchronicity and Serendipity Happen. Rochester, VT: Inner Traditions.

Friston, K. (2010). The free-energy principle: A unified brain theory? Nature Reviews Neuroscience, 11(2), 127–138. https://doi.org/10.1038/nrn2787

Good, P. I. (2005). Permutation, parametric, and bootstrap tests of hypotheses (3rd ed.). Springer.

Goodwyn, E. (2024). The innate story code. BioSystems, 244, 105285. https://doi.org/10.1016/j.biosystems.2024.105285

Jung, C. G. (1952). Synchronicity: An acausal connecting principle. Princeton University Press.

Kauffman, S. A. (1993). The origins of order: Self-organization and selection in evolution. Oxford University Press.

Kelso, J. A. S. (1995). Dynamic patterns: The self-organization of brain and behavior. MIT Press.

Livio, M. (2002). The golden ratio: The story of phi, the world's most astonishing number. Broadway Books.

Liu, J., Yu, C., Doherty, T. M., Akbari, O., Allard, P., & Rehan, V. K. (2020). Perinatal nicotine exposure-induced transgenerational asthma: Effects of reexposure in F1 gestation. FASEB Journal, 34(9), 11444–11459.

Miller, M. B., & Bassler, B. L. (2001). Quorum sensing in bacteria. Annual Review of Microbiology, 55, 165–199.

Mitchell, M. (2009). Complexity: A guided tour. Oxford University Press.

Nicolis, G., & Prigogine, I. (1977). Self-organization in nonequilibrium systems. Wiley.

Noble, D. (2012). Dance to the tune of life: Biological relativity. Cambridge University Press.

Pearson, K. (1900). On the criterion that a given system of deviations from the probable… Philosophical Magazine, 50, 157–175.

Pletzer, B., Kronbichler, M., Aichhorn, M., Bergmann, J., Ladurner, G., & Kerschbaum, H. (2010). Menstrual cycle and hormonal contraceptive use modulate human brain structure. Brain Research, 1348, 55–62.

Prigogine, I. (1980). From being to becoming: Time and complexity in the physical sciences. Freeman.

Rominger, C., Fink, A., & Perchtold-Stefan, C. M. (2024). Experiencing more meaningful coincidences is associated with more real-life creativity? Insights from three empirical studies. PLOS ONE, 19(5), e0300121. https://doi.org/10.1371/journal.pone.0300121

Roxburgh, E. C., Ridgway, S. & Roe, C. A. (2016). Synchronicity in the therapeutic setting: A survey of practitioners. Counselling and Psychotherapy Research, 16(1), 44–53. https://doi.org/10.1002/capr.12057

Russo-Netzer, P., & Icekson, T. (2023). An underexplored pathway to life satisfaction: The development and validation of the synchronicity awareness and meaning-detecting scale. Frontiers in Psychology, 13, 1053296. https://doi.org/10.3389/fpsyg.2022.1053296

Sacco, R. G. (2018). Fibonacci harmonics: A new mathematical model of synchronicity. Applied Mathematics, 9(6), 702–718.

Sacco, R. G. (2019). The predictability of synchronicity experience: Results from a survey of Jungian analysts. International Journal of Psychological Studies, 11(3), 46–62.

Sacco, R. G., Marks-Tarlow, T., & Beitman, B. D. (2026). Archetypes as codes: Jungian psychology, biological organization, and the fractal logic of synchronicity. International Journal of Jungian Studies. Advance online publication. https://doi.org/10.1163/19409060-bja10063

Silverman, B. W. (1986). Density estimation for statistics and data analysis. Chapman & Hall.

Strogatz, S. H. (2001). Nonlinear dynamics and chaos. Westview Press.

Torday, J. S. (2015). The cell as the mechanistic basis for evolution. Wiley Interdisciplinary Reviews: Systems Biology and Medicine, 7(4), 275–284. https://doi.org/10.1002/wsbm.1305

Torday, J. S. (2016). The cell as the first niche construction. Biology, 5(2), 19. https://doi.org/10.3390/biology5020019

Torday, J. S., & Miller, W. B. (2021). The Singularity of Nature: A Convergence of Biology, Chemistry and Physics. Royal Society of Chemistry.

Verrelli, C. M., Caprioli, L., & Bonaiuto, V. (2024). Cyclic human movements and time-harmonic structures: Role of the golden ratio in the tennis forehand. In R.

Montanari et al. (Eds.), Engineering methodologies for medicine and sports: Proceedings of EMMS 2024 (pp. 557–577). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-63755-1_42

Verrelli, C. M., Caprioli, L., & Iosa, M. (2025). Hidden time-patterns in cyclic human movements: A matter of temporal Fibonacci sequence generation and harmonization. Frontiers in Human Neuroscience, 19, Article 1525403.

Verrelli, C. M., Iosa, M., Roselli, P., Pisani, A., Giannini, F., & Saggio, G. (2021a). Generalized finite-length Fibonacci sequences in healthy and pathological human walking: Comprehensively assessing recursivity, asymmetry, consistency, self-similarity, and variability of gaits. Frontiers in Human Neuroscience, 15, Article 649533. https://doi.org/10.3389/fnhum.2021.649533

Verrelli, C. M., Romagnoli, C., Jackson, R., Ferretti, I., Annino, G., & Bonaiuto, V. (2021b). Phi-Bonacci butterfly stroke numbers to assess self-similarity in elite swimmers. Mathematics, 9(13), Article 1545. https://doi.org/10.3390/math9131545

West, G. B., Brown, J. H., & Enquist, B. J. (1997). A general model for the origin of allometric scaling laws in biology. Science, 276(5309), 122–126. https://doi.org/10.1126/science.276.5309.122