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Research Article

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Posted Date: November 20th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10772105/v1

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Additional Declarations: No competing interests reported.

From Opinion Leaders to Time Influencers:

How Do Users' Time Rhythms on Online Platforms Relate to Content Leadership?

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Abstract: In the real-time, fragmented, and rhythm-driven communication environment of digital platforms, **user influence depends not only on "who is speaking" and "what is being said," but also on "at what temporal rhythm it is being said. "** This study uses highly active users on the Toutiao platform as a sample. Based on two years of continuous user posting data, it employs power spectrum analysis and red noise testing to extract the periodic rhythmic characteristics of user posting behavior, and summarizes these characteristics through principal component analysis into dominant period concentration, period signal clarity, and period structural complexity. Building on this, the study employs non-negative matrix factorization to construct user content vectors. By combining cross-lagged correlation analysis with the Rozelle-Campbell baseline method, it identifies directed content-leadership relationships between user pairs and examines the influence of temporal rhythm relationship structures at three levels: the actor level, the shared level, and the proximity level. The findings reveal that the more balanced an actor's periodic energy distribution, the clearer their periodic signals, and the simpler their periodic structure, the more likely content-leadership relationships are to form between user pairs; simultaneously, the more substantial the common ground between agents and recipients in favorable temporal structures and the closer their rhythmic structures, the higher the likelihood of forming content-leadership relationships**.** The study indicates that **temporal rhythms are not merely an external context for platform-based communication but rather an important communicative resource embedded in user relationship structures that influences the generation of content. Consequently, this paper proposes the analytical perspective of "temporal influencers," supplementing the temporal dimension in opinion leader research and providing a relational explanation for understanding the generation of user influence on online platforms.**

Keywords: temporal rhythm; opinion leader; content leadership; temporal influencer; frequency-domain analysis

1. Problem Statement and Research Motivation

Time serves not only as a fundamental condition for online communication but also as a crucial dimension through which users engage in content expression, content diffusion, and relational interactions. Traditional communication research has long focused on "who speaks," "what is said," and "through which channels," but in the real-time, fragmented, and rhythm-driven communication environment of digital platforms, "when to speak" and "at what temporal rhythm" may equally influence whether content is seen, received, followed, or even imitated. User behavior on online

platforms is not entirely random or discrete; rather, it often exhibits recognizable temporal rhythms: some users post consistently at fixed intervals, some appear concentrated at specific time points, and others exhibit complex and multifaceted posting rhythms. This raises further questions: Are users' temporal rhythms merely a behavioral phenomenon in platform communication, or can they become a relational force that influences other users' content expression? In other words, can a temporal form shape a content form? The research in this paper stems primarily from the following two aspects.

First, research on media time has thoroughly revealed the temporal structures in digital communication but has relatively neglected discussion of the user role of "time influencers."

Existing research on media time has clearly demonstrated that time is not a neutral communicative backdrop, but rather a structural condition deeply embedded in media technology, platform mechanisms, and social order. Existing literature confirms that media technologies have driven the evolution of social temporal systems from natural and mechanical time to granular, hybrid, and fragmented media time, reshaping how users perceive and organize time (Chen, 2024; Bian, 2024; Zhang, 2024; Han, 2018). These studies collectively demonstrate that media technology has not only altered the speed and scope of information dissemination but has also transformed the ways in which users perceive, organize, and use time.

However, existing research on media time has largely focused on how media technologies, platform mechanisms, and social structures shape users' time, while relatively little attention has been paid to users as agents of time. On the one hand, relevant studies often start from the perspective of technology and platforms, emphasizing how media organizes, accelerates, or fragments users' time; on the other hand, analyses of users' time patterns frequently use platform types, demographic characteristics, or group categories as their basic units of analysis. The temporal structure of contemporary society has shifted from standardized time to a more flexible structure (Zheng, 2010), and users' media consumption also varies depending on platform rhythms and life contexts. Prior studies have documented temporal rhythm variations across demographic groups and platforms, yet they mostly rely on static group-level analysis rather than exploring individual-level stable posting rhythms and their relational consequences (Boczkowski et al., 2018; Stallings et al., 2022). Regarding content-driven relationships on digital platforms, the question truly worthy of further inquiry is: How do individual users develop stable, recognizable, and comparable temporal rhythms through long-term posting? And could these rhythms potentially influence other users' content expression?

Furthermore, existing research has already suggested that users' temporal rhythms do not exist in isolation but may have relational consequences. Through observations of the frequency distribution of call data, Song Zhu et al. "found that mobile phone users exhibit different levels of activity on weekdays and weekends" (Song et al., 2015). Takano viewed users' online communication rhythms as "combined oscillators" within complex social networks and found that users' rhythms may synchronize with those of their friends (Takano, 2023).Thulin and Vilhelmson's study on remote work also suggests that "pacesetters" emerge in horizontal interactions, disrupting the collective work schedule (Thulin & Vilhelmson, 2022).These studies illustrate that users' temporal rhythms are not isolated from one another but may exhibit phenomena of synchronization, coordination, or pacing. However, existing research on these relational consequences remains largely confined to the temporal domain—that is, it primarily reveals how "time may influence time"—without further exploring whether temporal rhythms spill over beyond the temporal domain itself into relationships involving content expression, content diffusion, and content leadership.

Research on temporal power offers another important clue for understanding the relationship between time and influence. Some studies have pointed out that political power achieves governance by "controlling time, space, the body, and daily life" (Zhang, 2013). This macro-level analysis of

temporal power simultaneously constructs a unidimensional framework for understanding power. In their critical reflections, subsequent researchers have emphasized that individuals are not entirely passive objects of time. Research on temporal politics shows that time operates both as a tool of institutional discipline and as a resource for individual agency and resistance (Scott, 2011; Sun & Chen, 2021), but horizontal temporal power dynamics among ordinary users remain under-explored. However, existing research on the politics of time has primarily focused on the vertical "institution/platform–user" relationship; in contrast, the horizontal, micro-level power dynamics through which ordinary users influence one another via temporal rhythms have yet to be fully explored. In other words, the influence—or even power—of temporal rhythms does not exist solely between institutions, platforms, and users; it may also exist between users themselves. Furthermore, temporal rhythms are not merely the result of users being shaped or self-adjusting; they may also serve as a resource through which ordinary users gain visibility and influence in horizontal interactions, thereby further shaping the dissemination of others' content. Consequently, research on temporal power must further explore the following question: In user relationships on digital platforms, can temporal rhythms transcend mere time management to actively participate in the generation of content expression, content diffusion, and content leadership?

In sum, existing media time research has confirmed the structural importance of time but has not yet identified the user role of "temporal influencers" who shape others' content expression via their posting rhythms — a core gap this study addresses.

Second, research on opinion leaders has already established a relatively mature explanatory framework centered on "influencers," but it lacks systematic consideration of the temporal dimension.

Classic opinion leader theory has long focused on how specific users influence others' perceptions and behaviors through their views, content, identity, social capital, or network position. On online platforms, concepts such as key opinion leaders and opinion influencers have been further applied to explain content diffusion, agenda-setting, and the formation of user-follower relationships. However, existing opinion leader research generally retains a strong "content-centric" bias. The opinion leader research paradigm in communication studies has long been dedicated to analyzing the pathways of information and opinion diffusion, often focusing on the content characteristics, social network characteristics, or audience characteristics of opinion leaders. Although this paradigm possesses strong explanatory power, it rarely systematically discusses the role of "temporality" in the construction of influence. In fact, as the algorithmic, fragmented, and real-time nature of online platforms has reshaped the fundamental rhythm of user interaction, the importance of "when to speak" and "at what temporal rhythm to speak" is no less significant than "what to say."Content does not exist in a vacuum. The same content posted at different times may achieve varying levels of visibility; similarly, the same viewpoints embedded in different posting rhythms may produce different diffusion effects. Wang Xingyuan and Liu Yun studied the relationship between the timing of corporate Weibo content posts and group excitement, finding that the group excitement effect triggered by content posted at different times also varies (Wang & Liu, 2022). This suggests that time is not merely an external context for content dissemination but may directly contribute to the generation of dissemination effects and user influence. Consequently, research on opinion leaders needs to expand from the content dimension to the temporal dimension. User influence does not necessarily stem solely from content authority, social prestige, follower size, or network centrality; it may also arise from a recognizable, sustainable, and perceptible temporal rhythm. Traditional theories of opinion leadership, if they overlook the temporal dimension, struggle to explain this phenomenon of content leadership driven by temporal patterns.

Given these shortcomings, this paper attempts to establish a connection between media time studies and opinion leader research: on the one hand, media time studies need to address the question of "who exerts influence over time"; on the other hand, opinion leader research needs to address the question of "how time constitutes influence." This paper therefore introduces the concept of "time influencers" to refer to users who can guide the content expression of other users through their own temporal rhythms. Unlike traditional opinion leader theories, which emphasize "who is speaking" and "what is being said," time influencers emphasize "at what temporal rhythm one speaks." This concept does not negate the importance of content, identity, and network position; rather, it further highlights that temporal rhythms themselves can also serve as a resource for communication and a source of influence. Consequently, the core research question of this paper can be formulated as follows: Do the temporal rhythm characteristics of users on online platforms influence the formation of content-leading relationships among users? Through a discussion of this question, this paper seeks to advance media time research from "how media shapes users' time" to "how users influence others through their temporal rhythms," and to expand opinion leader research from "opinion leader" to "temporal influencers," thereby providing a temporal explanatory framework for understanding user influence on digital platforms.

2. Variable Definitions and Hypotheses

2.1. Core Concepts and Variable Definitions

2.1.1. Temporal Rhythms of User Online Behavior

Users' online posting behavior is shaped by overlapping natural, cultural, social and psychological cycles, forming stable periodic temporal rhythms. This study focuses on posting behavior as the core dimension to measure users' temporal rhythms. **While "what" users say online is certainly important, "when" they say it is equally significant; therefore, we select the critical dimension of posting behavior to examine its temporal rhythms.** When and at what intervals users post constitute the key temporal rhythms of their digital participation. Although posting rhythms do not fully represent all of a user's temporal rhythms, as a "channel through which users proactively access information" (Lu et al., 2023), they facilitate our exploration of users' cyclical behaviors. Furthermore, posting behavior possesses its own distinct characteristics and significance. Posting behavior reflects users' social embeddedness and serves as a core channel for public discourse formation. With observable, socially connected and interactionally meaningful attributes, it is a reasonable entry point for examining the transmission mechanism of temporal rhythms. Therefore, posting behavior combines observability, social connectivity, and interactional significance, making it a reasonable entry point for studying the transmission and leadership mechanisms of temporal rhythms.

2.1.2. Key Dimensions of Temporal Rhythms: Oscillation Wavelength and Oscillation Intensity

This study defines users' "temporal rhythms" as comprehensive temporal patterns composed of the oscillation frequency (wavelength) at which their posting behavior exhibits significant periodicity and the oscillation intensity (amplitude) at each frequency (wavelength), thereby exploring the mechanisms by which the characteristic variables of temporal rhythms drive the establishment of content-leading relationships among users. The temporal rhythm of users' posting behavior is the underlying periodic "oscillation." Descriptions of oscillatory behavior typically focus on several fundamental dimensions: the wavelength and amplitude of the oscillation. These respectively pertain

to the frequency (wavelength) and intensity (amplitude) at which the cycle repeats.

On the one hand, wavelength relates to the cycle in which users operate—that is, whether it is the slow, agrarian rhythm of "the days when travel was slow by horse and cart" or the "time compression" of mechanical civilization and modern speed. It also relates to the pace of the "clock" underlying user behavior. This is a manifestation of "speed" on another level and is also an important aspect of the perception of time influenced by modern technology, as discussed by Paul Virilio in *Speed and Politics*. Theories such as "social acceleration" (Rosa, 2013) and "dromology" (Virilio, 2006) reflect the acceleration or transformation of society's rhythmic pace. Discourse aligned with the rhythm of "morning bells and evening drums" represents one wavelength and speed, while discourse aligned with the rhythm of "autumn's passing and spring's arrival" represents another. Different wavelengths or combinations thereof carry distinct natural, cultural, social, and psychological meanings; for example, the rhythms of the modern information society differ from the political and cultural functions of "beacon fires" used to transmit messages. The wavelengths inherent in internet users' posting behavior are far more complex than these typical speeds and rhythms, thus requiring specialized and detailed measurement; they may even include refined wavelengths such as 3 days, 14 days, or one-third of a week. Only through precise measurement can we accurately grasp the nature of user behavior in terms of wavelength and speed. Oscillation frequency reflects the speed of oscillation—that is, the number of periodic cycles completed per unit of time—which, in the context of this study, can be understood as the frequency with which users post on online platforms. The "wavelength" (or "period length") corresponding to a specific frequency can be calculated using the following formula: specific time span ÷ number of oscillations within that time span.

On the other hand, oscillation intensity (amplitude) reflects the intensity of periodic fluctuations at a specific wavelength. For example, at the same wavelength, a high amplitude indicates a loud volume and strong intensity, while a low amplitude indicates a soft volume and weak intensity despite the same timbre. It reflects whether a user's posting and discourse behaviors exhibit strong fluctuations at a specific periodic wavelength. This constitutes another important characteristic of a user's temporal rhythm—for instance, does a given user exhibit greater oscillation intensity in a 7-day cycle or a 3-day cycle? Among different users, who exhibits greater intensity in a 10-day cycle? These factors constitute important characteristics that distinguish one user from another. In terms of specific calculations, oscillation intensity refers to the degree of fluctuation of a physical quantity at a given frequency, typically measured by amplitude. Applied to this study, it reflects a user's posting volume at a specific periodic wavelength (e.g., every 7 days).

The two key parameters mentioned above—oscillation wavelength and oscillation intensity (amplitude)—can be quantified using classical frequency-domain analysis methods such as the power spectrum, and together they form the key framework for understanding the temporal rhythms of user posting behavior.

2.1.3. Measures of User Temporal rhythm Characteristics: Dominant Period Concentration (A1), Periodic Signal Clarity (A2), and Periodic Structural Complexity (A3)

Building on the previous definition of the temporal rhythms of users' online behavior, this paper further develops operational measures of the temporal rhythm characteristics in users' posting behavior. A user's posting behavior is not merely reflected in the number of posts or in being active or inactive at a given point in time; rather, it constitutes a temporal structure formed by multiple periodic oscillations and their energy distributions. In other words, the "temporal rhythm" of a user depends not only on whether they exhibit periodic posting behavior, but also on whether these periodic signals are clear, whether the energy of these cycles is concentrated, and whether their cyclical structure is

complex. Combining the fundamental attributes of periodicity and considering the two key factors of oscillation wavelength and oscillation intensity, the primary measurement indicators for users are as follows.

2.1.3.1. Dominant Cycle Concentration (A1). That is, does the user's posting behavior primarily revolve around a few prominent cycles? This dimension measures whether the user's posting rhythm is governed by one or a few "dominant rhythms." This attribute reflects whether a user's posting behavior is concentrated around a few core rhythms or is more dispersed across multiple rhythms.

2.1.3.2. Cycle Signal Clarity (A2). In other words, does the user's posting behavior exhibit distinct periodicity? This metric measures the purity and clarity of the user's behavioral rhythm. This attribute reflects the purity and regularity of user behavior as governed by one or more internal or external forces, with minimal "noise" from behavioral interference.

2.1.3.3. Cyclical Structure Complexity (A3). In other words, is a user's posting behavior composed of a few cycles, or is it the result of multiple overlapping cycles? This dimension measures the complexity of the internal structure of a user's temporal rhythms. This attribute does not reflect the quantity of a user's posts, but rather the number of periodic components underlying their posting rhythm and the complexity of the temporal structure formed by these components.

2.1.4. Measures of the Relationship Between Temporal Rhythmic Characteristics of Two Users: Agent Level (X1), Shared Level (X2), and Proximity (X3)

Users' temporal rhythm characteristics are first observed at the individual level. For example, a user's posting behavior may revolve primarily around a few fixed rhythms with relatively clear periodic signals, or it may exhibit a more complex periodic structure. However, this paper focuses not merely on the temporal rhythms of individual users, but on how these rhythms influence the relationships between users. In other words, content-driven relationships are not attributes of isolated individuals but occur within user pairs composed of "agents and recipients." Therefore, it is necessary to further transform individual-level temporal rhythm characteristics into variables capable of characterizing the relational status between two users. Based on this, this paper characterizes the temporal rhythm relationships between two users from three aspects: agent level (X1), shared level (X2), and closeness (X3).

The "Agent Level" (X1) dimension characterizes the level of a user acting as an agent in terms of a specific temporal rhythm. Since the content-driven relationship discussed in this paper has a clear directionality—A→B and B→A represent two different directions—in A→B, A is the agent and B is the patient; whereas in B→A, the roles are reversed. Therefore, understanding the temporal rhythm characteristics of users in the agent role is a crucial foundation for comprehending the formation of content-driven relationships. The "Agent Level" reflects the "temporal rhythm" of potential opinion leaders—that is, their temporal rhythm state as manifested in aspects such as the concentration of dominant cycles, the clarity of cyclical signals, and the complexity of cyclical structures.

The "Common Level" (X2) dimension characterizes the baseline level that both the agent and the patient share regarding a specific temporal rhythm feature. It does not reflect the temporal rhythm characteristics possessed by either party individually, but rather the relational foundation that both users can jointly achieve regarding the same rhythm feature. If both the active and passive parties possess a corresponding level of a particular rhythmic feature, that feature is more likely to become a shared condition in their relationship; if one party's level on that feature is lower, the shared relational

foundation between them on that dimension will be limited. Therefore, the "Common Level" emphasizes the "shared foundation" between users regarding rhythmic features, reflecting the logic of constraint by the weakest link in relationship formation.

The "Degree of Proximity" (X3) dimension characterizes the similarity between the agent and the patient regarding a specific temporal rhythm feature. The smaller the gap between two users on the same rhythm feature, the greater their similarity in that temporal rhythm structure; conversely, the larger the gap, the greater the relational distance between them on that rhythm feature.

2.1.5. Temporal Influencers and Content Leadership Capabilities, Content Leadership Relationships (Y1): From Opinion Leaders to Temporal Leaders

Building on the preceding discussion, key users who can establish content-leading relationships with other users through their own temporal rhythm characteristics (A1, A2, A3) can be defined as "temporal influencers" (temporal influencer). Drawing on the classic term "opinion leader," they can be referred to simply as temporal leaders. Compared to traditional roles and functions such as "Key Opinion Leaders (KOLs)," "public opinion influencers," and "interest leaders" (Xu, 2023)**, "temporal influencers" do not emphasize influence generated by social or content mechanisms—such as "who is speaking" or "what is being said"—but rather emphasize the content influence and content-leading ability generated through temporal rhythm characteristics, specifically "when to speak."**

Here**, "content leadership capability"** refers to a user's ability to cause other users' content expressions to become similar to their own and to be assimilated by them, thereby constraining and "setting" what other users "say" or "do not say." Within this capability, there exists a **"content leadership relationship"** (hereinafter referred to as Y1) at the micro level between any two users, which refers to the relationship in which the active user causes the passive user's content to become similar to and assimilated by the former.

High-level "time leaders" can, through their own powerful temporal rhythms or specific temporal patterns, cause other users' content to converge toward their own, thereby "setting" what other users "say" through "temporal forms." The necessity and importance of this role stem in part from the fact that the media's and users' temporal rhythms and forms may be linked to specific content preferences or communication frameworks and communication biases.

2.2. Formulation of Research Hypotheses

On online platforms, users do not express content in a completely random manner; rather, they form distinct temporal rhythm structures through long-term, repetitive posting behavior. In terms of content leadership relationships, temporal rhythms are not merely contextual conditions for user behavior; they may also constitute important relational conditions for users to be recognized, understood, and followed by others. In other words, the "temporal rhythm in which a user speaks" not only relates to the temporal form of their own content expression but may also determine whether their content will be received, imitated, and emulated by other users in subsequent time periods. Therefore, to understand how temporal rhythms drive the formation of content-leadership relationships, it is necessary to further examine which temporal structures are more easily recognized, adapted to, and transformed into content-leadership relationships among users.

Stable, recognizable and adaptable temporal rhythms are more likely to drive content-leadership formation than highly bursty or irregular patterns. Predictable rhythms reduce interaction uncertainty and sustain long-term engagement (Walther & Tidwell, 1995; Rempel et al., 1985), while overly concentrated bursty patterns limit the scope of information diffusion (Navarro et al., 2017; Miritello et

al., 2011).

It can thus be seen that a temporal rhythm characterized solely by high intensity or high bursts is not conducive to the formation of content-driven relationships. The characteristics of temporal rhythms that are conducive to the formation of content-driven relationships, as discussed in this paper, are primarily composed of three aspects: First, the distribution of energy over time is relatively balanced, meaning that users' posting rhythms do not rely excessively on a single or a few extremely prominent periodic peaks, thereby reducing the dependence of content expression on narrow time windows; Second, the periodic signals are relatively clear; that is, the periodic components in users' posting behavior are distinguishable from random noise, making their posting rhythms easier to identify and predict; third, the periodic structure is relatively simple; that is, users' posting behavior is not the result of a complex superposition of too many periodic components, thereby reducing the cost for other users to understand, adapt to, and follow their rhythms. Consequently, a more balanced, clearer, and simpler temporal rhythm collectively characterizes a relatively stable temporal structure. Its mechanism of action does not lie in simply increasing posting intensity, but rather in providing low-friction temporal conditions for the formation of content-leadership relationships by increasing opportunities for sustained engagement, enhancing temporal predictability, and reducing the cost of adapting to the rhythm.

Building on this foundation, this study derives hypotheses across three levels: the agent level, the co-activity level, and the proximity level. By distinguishing these three levels, this paper is able to further transform the characteristics of temporal rhythms at the individual level into relational variables at the user level, thereby examining how temporal structure contributes to the formation of content-led relationships.

First, from the agent level (X1), content-led relationships exhibit clear directionality: within a given user pair, the agent is the potential content leader, while the recipient is the party likely to be influenced by the agent's content. Therefore, the agent's own temporal structure serves as a crucial starting point for understanding the formation of content-led relationships. Existing research indicates that the timing of content publication is not a neutral communicative context but rather influences audience reactions and group arousal effects (Wang & Liu, 2022). This suggests that for potential influencers, "when they speak" and "at what temporal rhythm they speak" may in themselves affect the likelihood of their content being received and responded to. If an agent's posting rhythm is overly concentrated around a few periodic peaks, their content may generate a strong surge at specific time points; however, such an overly concentrated rhythmic structure may also narrow the time window during which their content can be consistently recognized and followed over the long term. In contrast, agents with a more balanced distribution of periodic energy can present their content within a more sustained temporal structure, thereby more easily establishing a posting rhythm that is recognizable and easy to follow. At the same time, the clearer the periodic signal, the more predictable the agent's posting behavior becomes, and the easier it is for recipients to grasp the temporal patterns of content appearance through repeated exposure. The simpler the periodic structure, the less likely the actor's temporal rhythm is to be obscured by the overlap of multiple cycles, and the easier it is for the recipient to understand and adapt to it. Based on this, this paper proposes the following hypothesis:

H1: The stability of the actor's temporal structure influences the formation of content-led relationships between users.

H1a: The lower the concentration of the actor's dominant cycle—that is, the more evenly distributed its cyclical energy—the easier it is for users to form a content-leadership relationship with the actor.

H1b: The higher the clarity of the agent's periodic signals—that is, the clearer the periodic

patterns in their posting behavior—the easier it is for users to form a content-leadership relationship with the agent.

H1c: The lower the complexity of the agent's periodic structure—that is, the simpler the rhythm of their posting—the more likely users are to form a content-leadership relationship between them.

Furthermore, content leadership relationships are not a natural spillover of the agent's unilateral attributes, but rather occur within the dyadic relationship formed between the agent and the recipient. Even if the agent possesses a relatively stable temporal structure, whether a content leadership relationship can form still depends on whether this temporal structure can constitute a common relational foundation at the user-pair level. Media time studies have long pointed out that ", 'broadcasting uses time as a medium and is deeply embedded in the temporal arrangements of modern society'" (Scannell, 1986). The temporal arrangements of the medium can provide actors with shared temporal coordinates and, on this basis, organize regulated information practices. At the micro level of user interaction, human communication activities themselves exhibit distinct rhythmic synchronization, and shared temporal rhythms constitute an important foundation for the unfolding of interaction (Morales et al., 2017); Takano's research on online social rhythms further reveals that the rhythms of online communication are not isolated from one another but may synchronize—and even spread across networks—through continuous connectivity (Takano, 2023). This indicates that users do not engage with content within completely separate temporal structures but, to a certain extent, share or adapt to a common temporal foundation. The "shared level" referred to in this paper emphasizes the foundational state jointly constituted by the actor and the recipient regarding a specific temporal rhythm characteristic. If the temporal rhythm structure between users lacks a common foundation, the actor's posting rhythm may be difficult for the recipient to consistently receive and adapt to, making it challenging to stably establish a content-led relationship.

Specifically, on the dimension of dominant cycle concentration, the higher the level of commonality between the actor and the recipient at highly concentrated cycle peaks, the more the user pair relies on a small number of prominent cycle nodes as a shared temporal foundation, and the more likely their content interaction is to be constrained by a relatively narrow time window; conversely, a lower level of commonality implies that the user pair relies less on highly concentrated cycle peaks as a shared rhythmic foundation, making it easier for the temporal structure of their relationship to maintain continuity. On the dimension of periodic signal clarity, if both the initiator and the recipient share relatively clear periodic signals, their posting behaviors exhibit high rhythmic recognizability, making it easier to establish relatively stable temporal expectations and conditions for content responses. On the dimension of periodic structure complexity, if both parties share relatively complex periodic structures, users face higher recognition and adaptation costs due to the superimposition of multiple cycles. Consequently, the common ground between the initiator and the follower regarding a relatively stable temporal structure may further influence the likelihood of forming a content-leadership relationship. Based on this, this paper proposes the following hypothesis:

H2: The shared level of stability in the temporal structures of the initiator and the follower will influence the formation of content leadership relationships between them.

H2a: The more balanced the periodic energy distribution jointly exhibited by the agent and the patient, the easier it is for users to form a content-led relationship between them.

H2b: The clearer the periodic signals jointly presented by the agent and the patient, the more likely users are to form a content-led relationship between them.

H2c: The simpler the periodic structure jointly exhibited by the agent and the recipient, the easier it is for users to form a content-led relationship between them.

Finally, in terms of proximity, users' perception of the content-led relationship between the agent and the recipient is also influenced by the degree of alignment between their temporal structures. Unlike the agent's level and the shared level, proximity emphasizes not the high or low level of a specific temporal rhythm feature itself, but rather the distance between the agent and the recipient on the same temporal rhythm dimension. Social network research has long shown that similarity itself is a crucial foundation for relationship formation and sustained interaction (McPherson et al., 2001). In communication relationships, homogeneity typically helps improve communication efficiency and the likelihood of mutual understanding (Rogers & Bhowmik, 1970). Therefore, when the agent and the recipient are more closely aligned in terms of temporal structure, they are more likely to develop similar temporal expectations and perceptions of rhythm, thereby reducing coordination costs during content reception, feedback, and follow-up. From the perspective of temporal coordination mechanisms, similar temporal structures can also reduce temporal conflicts and process losses during interactions. Mohammed and Harrison point out that when interacting parties exhibit excessive differences in their temporal orientations, the functioning of the relationship often entails higher levels of role mismatch, handover difficulties, and process losses (Mohammed & Harrison, 2013); research by Santos et al. on shared temporal cognition also indicates that when interacting parties share similar understandings and expectations of time, temporal conflicts are significantly reduced, and relational coordination becomes easier to achieve (Santos et al., 2016).It is evident, therefore, that the degree of similarity between the parties' temporal structures is not merely a static description of similarity, but rather a relational condition that can reduce the costs of rhythmic adaptation and enhance the coordinability of interactions. Based on this, this paper proposes the following hypothesis:

H3: The closer the agent and the recipient are in terms of temporal rhythm structure, the easier it is for users to form a content-led relationship.

In summary, this paper interprets a relatively stable temporal structure as a state of temporal rhythm jointly constituted by the balance of periodic energy distribution, the clarity of periodic signals, and the simplicity of periodic structure. It further proposes research hypotheses at three levels: the agent level, the shared level, and the degree of similarity. Through this framework of hypotheses (see Figure 1 for details), this paper transforms individual-level temporal rhythm characteristics into relational variables at the user-pair level, thereby examining how temporal structures contribute to the formation of content-led relationships.

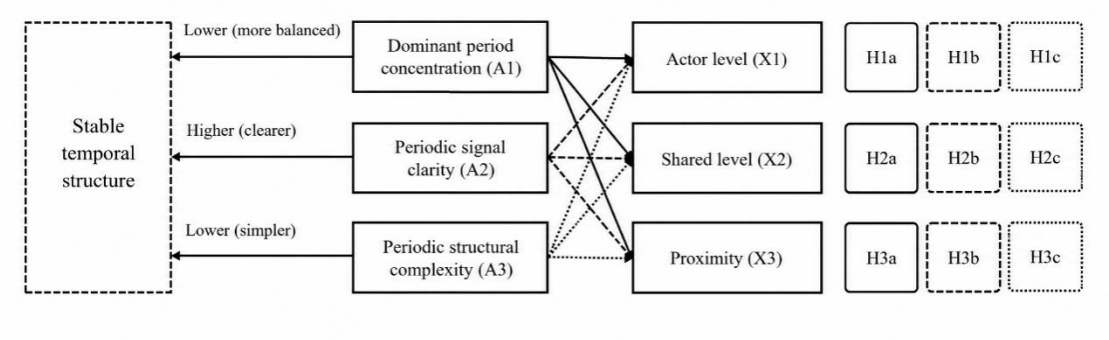


Figure 1 Schematic Diagram of the Hypothesis Framework

3. Empirical Design and Operationalization

3.1. Sample Selection and Data Preprocessing

This study uses data from the Toutiao platform. The final sample includes 2,953 active users, with an observation window spanning two consecutive one-year periods (July 2021 – June 2023). To control for heterogeneity in posting volume, 400 posts were randomly sampled per user per year to construct daily posting proportion series. All series were processed with a 7-day moving average and first-order differencing, and passed the ADF stationarity test.

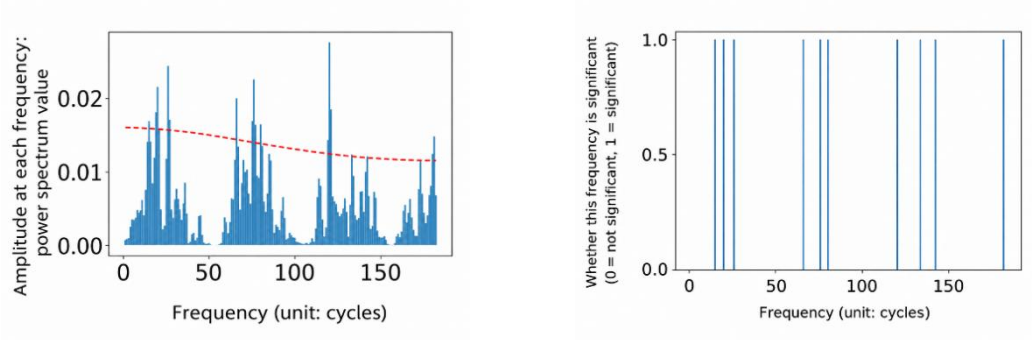
3.2. Identification of Significant Oscillation Frequencies in Users' Posting Rhythms

For the time series obtained above, power spectrum analysis was performed on the users' posting behavior time series to identify their periodic characteristics. Power spectrum analysis reveals the amplitudes of oscillation frequencies (wavelengths) at various periods within a time series. It is a commonly used classical method for identifying periodic signals and is widely applied across various disciplines, such as topic prediction in Chinese BBS forums (Nie, 2011) and the extraction of vocal aesthetic features (Zhang et al., 2023). This method is applicable to stationary time series, and when combined with the red noise test, it can extract significant frequencies (wavelengths).

Given a time series of length n, let m denote the maximum lag used in calculating the autocorrelation function; the level of detail in the power spectrum analysis varies with different values of m. If m is set too small, the analysis results will be overly "smoothed," making it difficult to capture the primary periodicity. Therefore, this study sets m to half the data length (i.e.,$\frac{n}{2}$) to strike a balance between detail and overall trends.

Power spectrum values can be calculated for each frequency. To distinguish true periodicity from random "noise-like" fluctuations, this study employs the red noise test as a criterion (Wei, 1999, pp. 78–79).The specific significance criterion is as follows: the power spectrum value calculated at that frequency must be a local peak (i.e., greater than the spectral values of the frequencies immediately to its left and right) and must exceed the standard spectral value generated by the red noise process at that frequency. Frequencies that satisfy both of these conditions are considered to exhibit statistically significant periodic oscillations.

Figure 2 shows the results of a user's significance frequency (period) analysis. Regarding the left panel of Figure 2: The horizontal axis represents the 182 calculated frequencies (where m is the integer value obtained by dividing 365 days by 2, resulting in 182); from left to right, these are 1, 2, 3…182. The wavelength corresponding to frequency f is 2*m/f. To distinguish meaningful periodicity from random fluctuations, this study adopted a red-noise significance test at the 0.05 level. On the vertical axis, the height of the solid line represents the power spectrum values, **while** the height of the dashed line represents the standard power spectrum values for red noise. **At the same position on the horizontal axis, if the height of the solid line is higher than that of the dashed line and the power spectrum value at that position is a local peak, it indicates that the period at that frequency is significant after passing the red noise test** (denoted as 1; otherwise, denoted as 0).Based on the left panel of Figure 2, the user's circadian rhythm is represented by a unique thermal code across 182 frequencies, resulting in a 182-dimensional circadian rhythm vector of the form [0,0,0,1,0,1,1,……], as shown in the right panel of Figure 2. Through power spectrum analysis and red noise significance testing, the significance distributions across 182 periodic frequencies were identified for 2,953 users.



left panel Right panel

Figure 2: Schematic illustration of periodic analysis of a user's time series

3.3. Definition and Operational Measurement of Users' Temporal-Rhythm Feature Variables

Based on the power spectrum analysis and red-noise test described above, this study quantified first-year users' temporal-rhythm features using 11 indicators. These indicators capture the dispersion of significant-period amplitudes, the strength of dominant peaks, the distribution of periodic energy, the clarity of periodic signals, and the richness of significant periods. Specifically, the indicators are: (1) standard deviation of amplitudes at significant periods, (2) maximum power-spectrum amplitude at significant periods, (3) mean squared power-spectrum amplitude at significant periods, (4) Gini coefficient, (5) sum of squared power-spectrum amplitudes at significant frequencies, (6) difference between the maximum and second-largest amplitudes at significant periods, (7) mean power-spectrum amplitude at significant frequencies, (8) signal-to-noise ratio, (9) mean squared FFT amplitude at significant periods, (10) number of period types, and (11) minimum power-spectrum amplitude at significant periods.

Because these first-year indicators differ in units, skewness, and sensitivity to extreme values, this study first applied a $\log_2(x+1)$ transformation to compress skewed distributions and reduce the influence of outliers, and then applied Z-score standardization to unify the measurement scale. For a small number of missing values, column medians were used for imputation. After preprocessing, principal component analysis (PCA) was used to reduce redundancy among the 11 indicators and extract comprehensive dimensions of users' first-year posting rhythms.

The data were suitable for dimensionality reduction. The Kaiser-Meyer-Olkin statistic was 0.616, exceeding the commonly used acceptability threshold of 0.60, and Bartlett's test of sphericity was significant (χ^2 = 49,752.283, df = 55, $p < .001$), indicating that the correlation matrix was not an identity matrix and that the indicators shared sufficient common structure. Following the Kaiser criterion of eigenvalues greater than 1, this study retained three principal components. Their eigenvalues were 5.197, 2.528, and 1.450, with explained variance rates of 47.23%, 22.97%, and 13.18%, respectively; the cumulative explained variance was 83.38%.

As shown in Figure 3, the three principal components correspond to different aspects of users' first-year posting rhythms. Principal Component 1 mainly loads on indicators related to the dispersion and peak concentration of significant-period amplitudes, including the standard deviation of significant-period amplitudes, maximum power-spectrum amplitude, mean squared power-spectrum amplitude, Gini coefficient, and the difference between the largest and second-largest amplitudes. It is therefore interpreted as dominant-period concentration or peak concentration: a higher score indicates that periodic energy is more concentrated around one or a few prominent peaks. Principal Component 2 mainly loads on the signal-to-noise ratio and the mean power-spectrum amplitude at significant

frequencies, and is interpreted as periodic-signal clarity: a higher score indicates that the user's periodic signal is clearer relative to noise. Principal Component 3 mainly loads on the number of period types and is interpreted as periodic-structure complexity: a higher score indicates that the user's posting rhythm contains more significant periodic components and is structurally more complex.

	Principal Component 1	Principal Component 2	Principal Component 3
Standard deviation of amplitudes at significant periods	0.983810924	-0.041165317	-0.040286634
Maximum power spectrum amplitude at significant periods	0.964732044	0.165161504	-0.059534658
Mean of squared power spectrum amplitudes at significant periods	0.884800866	-0.239961361	-0.021983233
Gini coefficient	0.882573087	-0.358921941	0.109657195
Sum of squared power spectrum amplitudes at significant periods	0.811084348	0.796371987	0.161023177
Difference between the largest and second-largest amplitudes at significant periods	0.749409705	-0.101943738	-0.198395231
Mean power spectrum amplitude at significant periods	0.311847835	0.785051195	-0.410709404
Signal-to-noise ratio	0.19298822	0.913821086	0.298385405
Mean of squared FFT amplitudes at significant periods	0.156386976	0.235633396	-0.512630165
Period types	-0.012054276	0.374153295	-0.857975099
Minimum power spectrum amplitude at significant periods	-0.597949396	0.631447902	-0.332504007

Figure 3: Principal Component Loadings of the 11 Temporal-Rhythm Indicators

3.4. Construction of User-Pair Temporal-Rhythm Variables: Actor Level, Shared Level, and Proximity

After PCA, each user obtained scores on the three temporal-rhythm dimensions. Because the dependent variable in this study is directional—whether user i forms a content-leadership relationship toward user j—the explanatory variables must be constructed at the directed user-pair level rather than only at the individual level. This study therefore transformed individual-level principal component scores into dyadic variables from three perspectives: actor level, shared level, and proximity.

Let user i be the actor, user j be the recipient, and the directed dyad be denoted as i → j. Let PC_ki and PC_kj denote the scores of user i and user j on temporal-rhythm component k, respectively, where k = 1, 2, 3. The actor-level variable captures whether the temporal structure of the potential content leader is associated with the formation of a content-leadership relationship and is defined as follows: $Actor_k_{ij} = PC_ki$

The shared-level variable captures the common temporal foundation jointly available to the actor and the recipient. Following the "weakest-link" logic, it is defined as the lower score of the two users on the same component: $\text{Shared_k}_{ij} = min(PC_ki, PC_kj)$

The proximity variable captures the similarity between the actor and the recipient on a given temporal-rhythm dimension. After standardizing the component scores, it is constructed from the absolute difference between the two users' scores, with higher values indicating greater proximity and lower values indicating larger distance: $Proximity_k_{ij} = 1 - |PC_ki - PC_kj|$

Taken together, each of the three principal components generates three dyadic explanatory variables: actor level, shared level, and proximity. The main model therefore includes nine temporal-rhythm relationship variables. In the main analysis, the shared-level variable is operationalized using the minimum value; alternative operationalizations, such as the sum of both users' scores, can be used as robustness checks.

3.5. Measurement of Content-Leadership Relationships and Model Specification

3.5.1. Vectorization of User-Posted Content

Content-driven influence is defined as a phenomenon of content feature assimilation that spans the temporal dimension, wherein the content preferences of the agent significantly influence the content preferences of the recipient after a period of time. This study employs the Non-Negative Matrix Factorization (NMF) algorithm (Lee & Seung, 1999) to perform dimensionality reduction and feature extraction on text data from any given user. The dimension of the NMF reduction was set to 100, resulting in a matrix of 2,953 users × 100-dimensional topics (see Figure 4). Each user's expression of a specific topic is encoded as a numerical vector representing the weights of the relevant topics; higher values indicate that the user's posted content carries greater weight for that topic.

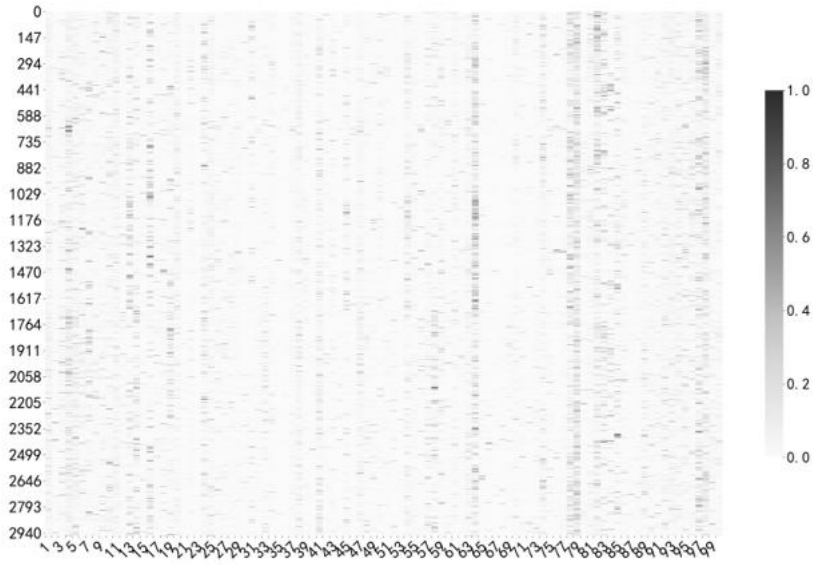


Figure 4: Embedding matrix of 2,953 users × 100-dimensional topics

*Figure caption: The horizontal axis (each column) represents the topic dimensions, while the vertical axis (each row) represents each user

The NMF dimension was set to 100. The TF-IDF vectorization used min_df = 80 and max_df = 0.7. This setting removes extremely rare terms that cannot support stable user-level comparison and excludes overly common terms that contribute little to topic discrimination. After dimensionality reduction, each user-year was represented by a 100-dimensional topic-weight vector. Table 1 presents the top keywords of selected topics. Although only 10 of the 100 topics are displayed due to space limitations, the keyword lists show that the topics are meaningfully distinguishable and can capture users' content characteristics.

Table 1: The 20 most important keywords for each topic after NMF-based dimensionality reduction

Topic	The 20 keywords with the highest TF-IDF values in this topic
Topic 1	Cross-talk, comedy, Guo Degang, Yue Yunpeng, Qian Ge, Yu Qian, not, no, myself, don't, just, we, classic, life, if, only, Victoria's Secret, what, others, secret
Topic 2	Food, Recommendations, TikTok, Restaurant Reviews, Chuzhou, Hot Pot, Check-in, Nanjing, Flavor, Delicious, Foodie, Internet Sensation, Jinling, Grilled Meat, Lobster, Trending, Meals, This Place, Together, Let's Go

Topic 3	Myself, Thank You, Like, Happiness, Life, That's It, A Day, Happy, Work Hard, Follow, Do Well, Support, One, Treat Well, Health, Definitely, Safety, Appearance, Everyone, Others
Topic 4	World, Mini, Survival, Parkour, Defeat, Magpie, Blocks, Lava, Players, I Can, Xiao Yu, Boss, Little Swallow, Mod, MC, The Void, Hamburger, Creatures, Rabbit, One
Topic 5	Story, Mystery Case, Strange Tales from a Chinese Studio, Folklore, Toy, Secret, Wife, Script, Murder Case, Widow, Comic Book, Scholar, Folk Tale, Repaying a Debt of Gratitude, Japanese Invader, Son, Fox Spirit, Old Man, Daughter-in-Law, Carpenter
Topic 6	Love Songs, Mortal World, Wedding Procession, Beauty, Soulmate, Passionate, West Sea, Longing, All the Way, A Kind, Northward, Missing Someone, In the Blink of an Eye, Koktokay, Shepherd, Time, Drunk, If, Butterfly, Many Years
Topic 7	Childhood, Light Music, 10, Relaxation, 12, Music, Leisure, Healing, Soothing, Sleep Aid, Refined, Calming, Green Mountains, Aesthetic, Comforting, Spiritual Cultivation, Elegant, 13, Classical, Mindfulness
Topic 8	Roundup, Those, Moments, Scenes, Awkward, All Over the Web, Surveillance, Funny, Hilarious, Humans, Live, Young Ladies, Beauties, Antics, Men, Caught Off Guard, Compilation, Series, Real, Moments
Topic 9	Cell Phones, Apple, Huawei, Xiaomi, Digital, iPhone, Digital Technology, 3C, 13, Must-Haves, Recommendations, Honor, OPPO, Snapdragon, Chinese-Made Phones, Series, Pro, Foldable, Price, OnePlus
Topic 10	Music, In-Car, Lossless, Hi-Fi, Sound Engineer, Authentic, Curated, Million, 10, Production, Full Version, Audiophile, Sound Quality, Classics, Charts, No. 1, Old Songs, 30, Great Songs, Share

3.5.2. Calculation of Directed Content-Leadership Relationships (Y1)

This study used cross-lagged correlation analysis to identify directed content-leadership relationships. This method, which is increasingly being applied in communication and social science research, can effectively identify the dynamic direction of influence between variables. For example, Su and Borah used this method to discover that social media exerts a "reverse latent influence" on the traditional media agenda during specific time periods (Su & Borah, 2019). Cross-lagged correlation analysis reveals underlying directions and trends of influence through predictive relationships in time series.

For each directed user pair $i \rightarrow j$, the Pearson correlation coefficient ρij was calculated between user$i$'s first-year 100-dimensional topic vector and user$j$'s second-year 100-dimensional topic vector:

$$\rho_{ij} = corr(C_{i,T}, C_{j,T+1})$$

Here, $C_{i,T}$denotes the first-year content vector of user$i$, and $C_{j,T+1}$ denotes the second-year content vector of user j. This design captures whether the content profile of a potential actor in the earlier period is associated with the content profile of a potential recipient in the later period.

To reduce the possibility of treating ordinary cross-sectional content similarity as leadership, this study further applied the Rozelle-Campbell baseline criterion (Cui, 2025; Hamaker et al., 2015). The baseline value for user pair $i \rightarrow j$ was calculated as follows:

$$B_{ij}^{RC} = \left[\frac{\rho(C_{i,T}, C_{j,T}) + \rho(C_{i,T+1}, C_{j,T+1})}{2}\right] \times \sqrt{\frac{\rho(C_{i,T}, C_{i,T+1})^2 + \rho(C_{j,T}, C_{j,T+1})^2}{2}}$$

In this formula, the first bracket captures the average synchronous content similarity between users i and j in the two periods, while the square-root term captures the average temporal stability of each user's own content profile. A directed relationship $i \rightarrow j$ was coded as Y_{ij}= 1 only when $\rho_{ij}$was positive, statistically significant, and greater than $B\frac{RC}{ij}$; otherwise, Y_{ij}= 0. The resulting matrix is a

directed binary content-leadership matrix.

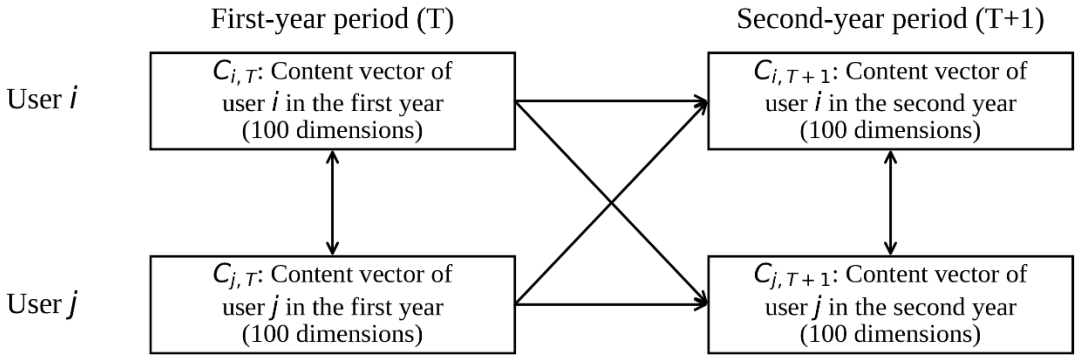


Figure 5: Schematic of Cross-Lagged Correlation Analysis

After excluding self-pairs, the final dyadic dataset contains 8,717,256 directed user-pair observations among the 2,953 users. Among these observations, 792,644 user pairs were identified as content-leadership relationships based on the cross-lagged correlation and Rozelle-Campbell baseline criteria, corresponding to a matrix density of 9.09%. Reporting this density is necessary because content-leadership ties are expected to be sparse, and the level of class imbalance affects subsequent model estimation and interpretation.

3.5.3. Logistic Regression Model and Robustness Strategy

To examine how temporal-rhythm structures relate to the formation of directed content-leadership ties, this study estimated a logistic regression model in which the dependent variable is Y_{ij}. The main explanatory variables include the actor level, shared level, and proximity for each of the three temporal-rhythm principal components. Because the dependent variable is sparse and the dyadic observations are highly imbalanced, the logistic regression was estimated with a class-weight-balanced strategy rather than by drawing a balanced subsample. This allows all directed user-pair observations to remain in the analysis while increasing the contribution of the relatively rare positive ties during model estimation.

4. Hypothesis Testing

All dyadic predictors are coded into tertiles (1 – 3) to mitigate extreme value bias. The VIF values range from 1.15 to 2.24, indicating no severe multicollinearity. The overall model is statistically significant (LR test, $p < .001$), supporting the joint explanatory power of temporal-rhythm variables.

Table 2: Results of the Regression Analysis

Variable	VIF	Beta (SE)	OR [95% CI]	p / Sig.
PC1 Dominant-period concentration (Actor)	1.53	-0.023 (0.004)	0.977 [0.970, 0.984]	p < .001 ***

PC2 Periodic-signal clarity (Actor)	1.43	0.012 (0.003)	1.012 [1.005, 1.019]	p < .001 ***
PC3 Periodic-structure complexity (Actor)	1.45	-0.064 (0.003)	0.938 [0.931, 0.944]	p < .001 ***
PC1 Dominant-period concentration (Shared level)	1.48	-0.065 (0.003)	0.937 [0.930, 0.943]	p < .001 ***
PC2 Periodic-signal clarity (Shared level)	2.24	0.154 (0.004)	1.166 [1.156, 1.176]	p < .001 ***
PC3 Periodic-structure complexity (Shared level)	1.96	-0.085 (0.004)	0.918 [0.911, 0.925]	p < .001 ***
PC1 Dominant-period concentration (Proximity)	1.15	0.121 (0.003)	1.129 [1.122, 1.136]	p < .001 ***
PC2 Periodic-signal clarity (Proximity)	1.72	0.010 (0.004)	1.010 [1.003, 1.017]	p = 0.007 **
PC3 Periodic-structure complexity (Proximity)	1.45	0.053 (0.003)	1.054 [1.047, 1.062]	p < .001 ***

At the actor level, balanced energy distribution, clear periodic signals and simple rhythm structure all positively predict content-leadership ties, supporting H1. At the shared level, the common temporal foundation between users shows a stronger positive association, supporting H2. At the proximity level, higher similarity in temporal structure increases the likelihood of leadership ties, supporting H3.

Overall, the empirical results support the three-level framework of actor level, shared level, and proximity. The role of temporal rhythms in content leadership is not a simple logic of greater intensity, but a relational logic of structural recognizability and alignment. A more balanced, clearer, and simpler temporal structure, together with greater proximity between the actor and the recipient, constitutes the temporal condition under which content-leadership ties are more likely to form.

5. Conclusion and Discussion

This study focuses on the temporal rhythms of users on online platforms and examines how these rhythms are associated with the formation of content-leadership relationships within directed user-pair structures. Using frequency-domain analysis, the paper identifies significant periodic components in users' posting behavior and summarizes them into dominant-period concentration, periodic-signal clarity, and periodic-structure complexity. It then constructs actor-level, shared-level, and proximity variables at the dyadic level and tests their relationship with directed content-leadership ties. The findings show that users are more likely to form content-leadership relationships when the actor's temporal rhythm is more balanced, clearer, and simpler, when both users share a more favorable temporal foundation, and when their temporal structures are closer.

First, from the perspective of media time studies, this paper advances "time" from a contextual condition of communication activities to an explanatory variable for the generation of user influence.

Users are not merely objects shaped by the platform's temporal structure; they may also form recognizable patterns of temporal action through their own stable, clear, or complex posting rhythms.

Second, from the perspective of rhythm studies, this paper expands the relational consequences of user temporal rhythms from "time influencing time" to "time influencing content." Existing research has noted the potential for rhythmic synchronization, temporal coordination, or rhythm leadership among users, but related discussions have primarily remained confined to the temporal domain. This paper further demonstrates that the role of temporal rhythms extends beyond influencing another user's time management; it may also spill over into the realm of content, participating in the generation of relationships involving content expression, content diffusion, and content leadership. Consequently, this paper provides empirical support for understanding "how temporal forms influence content forms."

Third, from the perspective of time power studies, this paper extends the discussion of time power from vertical control and resistance to horizontal user relationships. Among ordinary users on digital platforms, horizontal micro-level influences based on temporal rhythms also exist. Through their own posting rhythms, cyclical structures, and temporal consistency, users may gain the ability to influence others' content expression in horizontal interactions.

Fourth, drawing on research on opinion leaders, this paper expands the study of influence from a "content-centric" perspective to include the temporal dimension. Traditional research on opinion leaders primarily focuses on what users "say," what identities they possess, and what positions they occupy within the network, while rarely discussing how "when they speak" and "at what temporal rhythms they speak" contribute to the formation of influence. This paper introduces the concept of "temporal influencers," emphasizing that user influence does not stem solely from content, identity, or network centrality, but may also arise from identifiable, sustainable, and perceptible temporal rhythms. Consequently, building upon traditional opinion leader theory, this paper adds a temporal dimension to the understanding of platform user influence.

Fifth, regarding the mechanisms of influence generation, this paper shifts the research perspective from the attributes of individual nodes to binary relationship structures. Through three dimensions—actor level, shared level, and proximity—this paper demonstrates that temporal influence depends not only on the actor's own rhythmic characteristics but also on the temporal rhythmic relationship structure between the two parties. Consequently, this paper provides a relational perspective to explain "why the same user exerts influence only on specific targets."

Furthermore, for platform governance, temporal rhythm analysis can inform content ecosystem regulation and potential opinion leader identification. Users' posting rhythms, cyclical structures, and temporal relationships between users may influence the formation of content-leading relationships.

Limitations include potential sampling bias from the 400-post sampling design and the generalizability of single-platform findings. Future research could verify the robustness of results across larger samples and multiple platforms.

Statements and Declarations

Funding

National Social Science Fund of China, entitled Oscillating Strings: Research on the Periodic Changes and Regulation of Public Opinion Topics on Social Media, 24FXWB039.

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