Journal of Trends in Arts and Humanities
Print ISSN: 3007-7362
Online ISSN: 3007-7370
DOI: https://doi.org/10.61784/jtah3056

POPULAR MUSIC, DIGITAL INTERACTION RITUALS, AND GENERATIONAL WELL-BEING

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Abstract: Digital listening environments have turned popular music into a recurring social encounter rather than a purely private act of consumption. Using Randall Collins' Interaction Ritual Chains (IRC) as the interpretive frame, this paper examines whether comment-based music engagement is associated with subjective well-being and whether that association differs by generation and platform design. The empirical material comprises 10,215 cleaned comments drawn from more than 13,000 entries attached to 260 songs on NetEase Cloud Music, QQ Music, and TikTok Music, together with cross-generational and three-month longitudinal observations. A platform-adapted sentiment lexicon, emoji-weighted scoring, interaction-network indicators, topic modeling, and regression-oriented comparisons were used to translate shared attention, emotional entrainment, and symbolic boundaries into measurable variables. The older cohort, born in the 1970s and 1980s, displayed a stable upward emotional trajectory in nostalgia-centered settings: positive comments reached 82%, and the change on NetEase Cloud Music was highly significant ($p<0.01$). Users born in the 1990s and 2000s showed sharper short-term variation, including an initial mean stress response of $M=-0.3$, but recovered significantly on the short-video platform ($p<0.05$). Across three months, traditional community-oriented platforms were associated with a 23% rise in emotional energy among older listeners, whereas algorithm-led environments improved recovery efficiency among younger listeners by 40%. The evidence supports a generationally differentiated pathway from music interaction to emotional resonance and then to well-being. It also indicates that nostalgic memory functions may be especially useful for older audiences, while fast, adaptive emotion-regulation features are better aligned with younger users.
Keywords: Interaction ritual chains; Popular music; Sentiment analysis; Subjective well-being; Digital music platforms

1 INTRODUCTION

The circulation of cultural material has accelerated alongside globalization and networked media. Music now moves across borders, devices, and social settings with little friction, and its social meaning is produced as much through digital participation as through the sound recording itself [1]. Popular music is especially important in this shift. Its immediate emotional appeal, broad accessibility, and close relation to everyday identity have made it a common resource for recalling the past, articulating the present, and locating oneself within a group [2]. Streaming and short-video services intensify these functions by attaching comments, likes, shares, replies, and algorithmic recommendations to the act of listening.

This transformation changes the analytical question. It is no longer sufficient to ask what a song communicates or whether listeners enjoy it. The relevant issue is how repeated encounters around music create emotional momentum. Popular music developed from twentieth-century commercial forms, initially associated strongly with Western and particularly American industries, into a global cultural language supported by recording technology, broadcasting, and data-driven distribution [3]. Within contemporary platforms, charts and celebrity culture remain influential, but user participation now adds a second layer of meaning. Listeners narrate memories, seek recognition, echo one another's phrases, and publicly regulate mood. Music consequently operates as entertainment, an identity marker, a means of catharsis, and a social technology for everyday affective management [4-5].

Interaction Ritual Chains theory provides a useful way to interpret these practices. Collins argues that recurring rituals generate emotional energy when participants share attention, align their affective responses, recognize common symbols, and maintain a boundary between those who belong to the interaction and those who do not [6]. Physical co-presence is not the only route to such effects. In digital settings, temporal proximity, repeated symbols, reply structures, and visible reactions can produce recognizable forms of collective involvement [7]. Music services offer a particularly dense setting for this process. A comment can trigger replies; likes confer social recognition; repeated lyrics or memories become group symbols; and platform-specific language marks community membership. Through these small exchanges, users may convert individual listening into a shared emotional event [8-9].

Three gaps remain in the literature. First, work on online musical emotion often treats communication as a one-way transmission from content to listener. That approach underestimates the reciprocal activity through which emotional energy is accumulated in comment threads. Second, generational studies commonly describe differences in taste but say less about differences in expressive rhythm, symbolic language, and the route from interaction to well-being. Third, predominantly cross-sectional evidence cannot establish whether a favorable emotional response fades quickly or becomes more durable through repeated participation. These omissions matter because the same platform feature may support long-term nostalgic continuity for one cohort while enabling moment-to-moment mood repair for another.

The present research addresses these issues through a computational and longitudinal reading of digital music rituals. Sentiment scoring is combined with regression-oriented comparisons and operational indicators derived from IRC. The analysis spans comments connected to music from the 1970s through the 2000s and compares NetEase Cloud Music, QQ Music, and TikTok Music. Cross-generational distributions are examined alongside three months of repeated observation [10-11]. This design makes it possible to separate relatively stable emotional accumulation from short-lived but adaptive fluctuations without abandoning the social meaning of the interaction.

The paper makes three contributions:

It develops a dual analytical framework in which sentiment measurement and regression-oriented comparison quantify the emotional consequences of musical interaction.

It links generational comparison to repeated observation, revealing both cohort-specific emotional patterns and platform-specific temporal effects.

It extends IRC into digital music sociology through a measurable pathway from music interaction to emotional resonance and then to well-being.

2 RELATED WORK

2.1 Interaction Rituals Beyond Physical Co-Presence

IRC has been used to explain how shared practices produce solidarity, confidence, and durable symbols. Research on crisis response, for example, interprets infrastructure work, mutual assistance, and routine preventive action as participatory rituals capable of strengthening national identification [12]. The lesson is not that formal symbolism is irrelevant, but that emotional commitment becomes credible when people repeatedly take part in recognizable practices. At the interpersonal scale, successful rituals similarly generate emotional energy: recurring celebrations and mundane routines can synchronize partners' expectations and deepen relational attachment [13].

Online interaction complicates the original emphasis on bodily co-presence. Yet evidence from virtual settings shows that meaningful ties can emerge when participants share a focus, respond within a common temporal frame, and recognize the same symbolic repertoire [7]. Digital music platforms contain all three conditions. The song supplies a focal object; replies and danmu create a rhythm of mutual attention; and lyrics, performer identities, emojis, or memories provide portable symbols. These features make music comment spaces plausible sites of ritual production rather than passive archives of audience reaction.

2.2 Music as an Emotional and Social Resource

A substantial literature treats music as a psychosocial resource. Among older adults with depression, structured music-therapy programs have been linked to reductions in depressive symptoms and to improvements in psychological, cognitive, and emotional functioning [14-15]. Studies involving adolescents and young adults likewise report that attentive listening, lyric reflection, guided musical mindfulness, and respiration synchronized with music can support regulation and resilience [16-17]. These findings are not interchangeable with evidence from ordinary platform use, but they establish a credible basis for expecting music to influence affect through more than simple preference.

The route to well-being is also social. A qualitative investigation of Pakistani university students (N=9) found that listeners deliberately selected genres and lyrics to match or alter mood, used music to sustain concentration, and experienced it as a bridge across linguistic and cultural boundaries [18]. Community-based music initiatives have been associated with both personal recovery and stronger collective connection [19]. In a separate eight-week intervention involving 256 participants, 78% reported less stress; emotional resilience improved, and the mediation effect on employability outcomes was 44% [20]. Music-festival research further indicates that perceived musical quality and environmental atmosphere influence emotion and social identification, with consequences for young people's subjective well-being [21].

2.3 Position of the Present Research

The studies above explain why music can regulate emotion, but they do not fully capture the generational organization of everyday platform rituals. The present analysis therefore moves from clinical or event-based intervention to naturally occurring digital participation. It combines a cross-platform comment corpus covering five decades of musical material with a three-month observation frame. The central proposition is that well-being does not follow from exposure alone. It is shaped by how listeners gather around a song, how closely their emotional expressions align, and how platform conventions sustain or interrupt that alignment. The inquiry thus joins computational text analysis to a sociological account of repeated interaction.

3 METHOD

3.1 Research Design and Sampling Layers

The research uses two complementary dimensions. The cross-sectional dimension compares older users, born in the 1970s and 1980s, with younger users, born in the 1990s and 2000s, across NetEase Cloud Music, QQ Music, and

TikTok Music. The experimental framework initially allocates 30 comment samples per platform across the two broad cohorts. A controlled platform-by-decade subset contains 15 tracks from each of four decades on each platform, producing 180 tracks, and a behavioral frame of 120 participants, or 10 users in each platform-decade cell. The longitudinal dimension follows recurrent emotional expression over three months. The source records a broader 100-account tracking pool, while the purposively balanced focal subsample contains 60 identified users; the results section also reports trajectories on the 120-user behavioral frame. These counts are retained according to their stated analytical roles rather than silently collapsed into a single sample.

The full corpus was assembled from 260 representative songs released between the 1970s and 2023. For the decade-stratified sampling frame, 65 songs were selected from each of the 1970s, 1980s, 1990s, and 2000s. The top 50 comments by likes were retrieved for each track between January and March 2024, giving more than 13,000 raw entries. Duplicate posts by the same account under the same song were removed, as were comments shorter than three characters, advertising text, copied lyrics, and other non-analytic material. The cleaned cross-sectional corpus contains 10,215 comments. Younger cohorts are more prominent in this sample, consistent with the user composition of mainstream Chinese streaming services. Geographically, activity is concentrated in coastal and central provinces, with fewer observations from western and rural areas (Table 1).

Table 1 Demographic Distribution of Sampled Users (N=10,215)

Platform	Post-70s/80s	Post-90s/00s	Gender (M/F/U)	Top three regions
NetEase Cloud Music	38%	62%	48%/42%/10%	Guangdong, Beijing, Zhejiang
QQ Music	42%	58%	52%/38%/10%	Guangdong, Sichuan, Jiangsu
TikTok Music	28%	72%	45%/44%/11%	Guangdong, Henan, Shandong

Figure 1 summarizes the two-dimensional logic. Its first branch compares generational distributions at a given time; its second branch evaluates within-user emotional movement. In the original analytic notation, SLC denotes Sentiment Lexicon Construction, ISDA denotes Intergenerational Sentiment Distribution Analysis, OSLA denotes Optimized Sentiment Lexicon Application, and IGDTM denotes Individual-Group Dual-Trajectory Modeling.

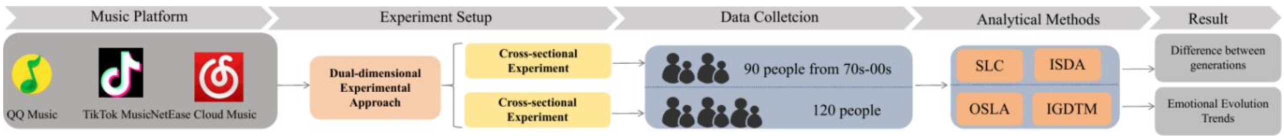

Figure 1 Cross-Sectional and Longitudinal Experimental Workflow

3.2 Preprocessing and Feature Representation

Python-based crawlers accessed publicly available interfaces on the three services. Standard natural-language processing removed stopwords, punctuation, and non-linguistic symbols; emojis were preserved because they carry affective information that would be lost in a text-only pipeline. User identifiers were replaced with cryptographic hashes. The source describes an initial MD5 procedure and a later SHA-256 implementation; the latter is the privacy protection applied to the refined corpus. Each comment was represented through temporal, textual, and social attributes. Temporal fields include posting time and reported listening duration. Textual fields record length, emoji frequency, and reply depth. Social fields include likes, shares, and direct mentions. Together, these variables capture persistence, expressive intensity, and public reinforcement (Table 2).

Table 2 Feature Groups Used to Represent User Comments

Feature group	Recorded content	Illustrative form
Temporal	Timestamp; listening duration	Posted at 13:13 on January 20; listening time of 900 hours
Textual	Word count; emoji use; reply depth	"This music sounds great" plus a smiling emoji
Social	Likes; shares; @mentions	@xxxx: "It is just like heaven"

3.3 Sentiment Measurement

Sentiment classification begins with the Dalian University of Technology Emotion Lexicon and extends it with recent slang, danmu expressions, and platform-specific usages [22]. The first score assigns each affect-bearing token an intensity weight and reverses the sign when the token falls within a negated phrase. If a comment contains n sentiment-bearing tokens, its lexical emotion score is:

$$EmotionScore(c) = \Sigma(i = 1 \ldots n) w_i \delta_i \quad (1)$$

Here w_i is the intensity of token i, while δ_i equals -1 under negation and +1 otherwise. A second formulation incorporates both the polarity s_i, bounded from -5 to +5, and the relative use of emojis. The emoji index is the number of emojis divided by the number of words; its empirically selected coefficient is β=0.3.

$$Sentiment(c) = \Sigma(i = 1 \ldots n)(w_i s_i) + \beta \cdot EmojiScore(c), \beta = 0.3 \quad (2)$$

The Emotion Ontology (EMO) supplies seven categories: joy, good, sorrow, anger, fear, surprise, and disgust. Joy and good are treated as positive; the remaining five are treated as negative. This grouping supports both detailed category comparison and a compact positive-comment ratio.

3.4 Operational Measures Derived from IRC

Three IRC components were translated into quantitative indicators. Shared focus is represented first by comment density. For song s, the total number of comments C_s is divided by the number of days T_s over which the comments were accumulated:

$$D_s = C_s/T_s \tag{3}$$

Density captures the intensity of collective attention, while Latent Dirichlet Allocation is applied to the top 10% of comments by engagement to identify the symbolic themes around which that attention converges [23]. Emotional entrainment is evaluated through a directed reply graph G=(V,E). A node represents a user, and a directed edge indicates that one user replied to another. Average in-degree and the clustering coefficient describe reciprocal involvement; Pearson's r between temporally adjacent sentiment scores measures local affective alignment.

Boundary maintenance is assessed through cohort-specific n-gram distributions P_g(n). Jensen-Shannon divergence compares the language used by age group g with that used by age group h:

$$JSD(P_g||P_h) = ½D_KL(P_g||M) + ½D_KL(P_h||M), M = ½(P_g + P_h) \tag{4}$$

D_KL denotes Kullback-Leibler divergence [24]. A larger JSD indicates that the cohorts rely on more distinct linguistic repertoires, which is interpreted as a stronger symbolic boundary between emotional communities [25].

3.5 Validation, Statistical Comparison, and Ethics

Two trained coders independently annotated a stratified random sample of 1,200 comments using the EMO framework. Agreement was high: the source reports Cohen's κ above 0.85 in the lexicon-validation stage and κ=0.87 for the final gold-standard set. Against that set, the rule-based, platform-adapted classifier achieved F1=0.89. Longitudinal inference uses mean sentiment on a -3 to +3 scale, the share of comments classified as joy or good, and paired t-tests comparing Month 1 with Month 3. The design is correlational; regression modeling is used to assess association, not to claim experimentally identified causation. Data were drawn from official or publicly accessible interfaces, identifiers were anonymized, and the analysis followed ethical data-use procedures.

4 RESULTS AND DISCUSSION

4.1 Cross-Sectional Emotional Distributions

Positive categories occupy the largest combined share on all three platforms, but the balance between joy and good differs by cohort. On NetEase Cloud Music, joy accounts for 33.30% of younger-cohort comments and 23.30% of older -cohort comments. The pattern reverses for good: 33.33% among older users and 20.00% among younger users. QQ Music is more even. Joy represents 24.51% for the younger cohort and 27.30% for the older cohort, while good again appears more frequently among older users (33.33% versus 21.22%). TikTok Music produces the clearest older-cohort advantage in joy, 36.66% compared with 25.22%; good is closer, at 27.88% and 22.22%, respectively (Table 3).

Table 3 Emotion-Category Distributions by Platform and Cohort

Platform	Emotion	Post-90s/00s	Post-70s/80s	Polarity
NetEase Cloud Music	Good	20.00%	33.33%	+
NetEase Cloud Music	Joy	33.30%	23.30%	+
NetEase Cloud Music	Disgust	6.67%	14.30%	-
NetEase Cloud Music	Fear	6.67%	7.30%	-
NetEase Cloud Music	Anger	6.67%	7.30%	-
NetEase Cloud Music	Surprise	6.67%	10.00%	-
NetEase Cloud Music	Sadness	20.00%	4.47%	-
QQ Music	Good	21.22%	33.33%	+
QQ Music	Joy	24.51%	27.30%	+
QQ Music	Disgust	9.66%	6.67%	-
QQ Music	Fear	9.57%	4.00%	-
QQ Music	Anger	11.11%	6.67%	-
QQ Music	Surprise	12.96%	10.00%	-
QQ Music	Sadness	10.97%	16.70%	-
TikTok Music	Good	22.22%	27.88%	+
TikTok Music	Joy	25.22%	36.66%	+
TikTok Music	Disgust	6.67%	11.37%	-
TikTok Music	Fear	12.22%	10.00%	-
TikTok Music	Anger	8.66%	4.70%	-
TikTok Music	Surprise	11.01%	4.70%	-
TikTok Music	Sadness	14.00%	4.70%	-

Note: + indicates positive affect; - indicates negative affect

Negative emotion is more unevenly distributed. NetEase Cloud Music contains a marked sadness gap: 20.00% for younger users and 4.47% for older users. Older users, however, register more disgust (14.30%) and surprise (10.00%). On QQ Music, younger users show more anger (11.11%) and fear (9.57%), whereas sadness is higher for the older cohort (16.70%). TikTok Music again shows more sadness among younger listeners, 14.00% versus 4.70%, while fear and disgust are comparatively closer. The pattern is therefore not a simple opposition between positive older users and negative younger users. It is a difference in emotional composition and volatility.

From an IRC perspective, older listeners appear to draw on a stable archive of shared memory. Familiar songs reactivate durable associations, and comment exchanges reinforce a recognizable group narrative. Their positive expression is often reflective and cumulative. Younger listeners combine positive response with sharper movements in sadness, anger, fear, and surprise. Emojis, slang, hyperbole, and rapid replies make the interaction more situational. In this case, the platform functions less as a storehouse of ritual continuity and more as an interface for immediate emotional adjustment.

4.2 Three-Month Sentiment Trajectories

Table 4 reports the monthly sentiment scores and positive-comment ratios. The older cohort rises steadily on every service. NetEase Cloud Music moves from +1.8 to +2.1 and then +2.4, with 82% positive comments. QQ Music progresses from +1.6 to +1.9 and +2.2, with 78% positive comments. TikTok Music advances from +1.7 to +2.0 and +2.3, with 80% positive comments. The table in the source labels the younger block as 80s-90s, while the surrounding analysis defines it as the 1990s-2000s cohort; the numerical values are reproduced without alteration. In that block, all three services fall in Month 2 and recover in Month 3.

Table 4 Sentiment Trends on Three Platforms over Three Months

Cohort	Platform	Month 1	Month 2	Month 3	Positive ratio
70s-80s	NetEase Cloud Music	+1.8	+2.1	+2.4	82%
70s-80s	QQ Music	+1.6	+1.9	+2.2	78%
70s-80s	TikTok Music	+1.7	+2.0	+2.3	80%
90s-00s	NetEase Cloud Music	+1.2	+0.5	+1.5	65%
90s-00s	QQ Music	+1.0	+0.3	+1.2	60%
90s-00s	TikTok Music	+1.1	+0.2	+1.4	62%

The corresponding Month 1-to-Month 3 changes clarify the contrast. NetEase Cloud Music and QQ Music each increase by +0.6 for older users, while TikTok Music increases by +0.5. The NetEase result is highly significant ($p<0.01$); the QQ and TikTok changes are significant at $p<0.05$. Younger users record smaller net improvements: +0.3 on NetEase, +0.2 on QQ Music, and +0.3 on TikTok Music. Only TikTok reaches $p<0.05$. NetEase ($p=0.12$) and QQ Music ($p=0.25$) do not cross the significance threshold. The source table describes the NetEase younger-cohort interpretation as a significant increase while also marking it with a right arrow; because $p=0.12$, the statistically consistent reading is a positive but non-significant change (Table 5).

Table 5 Longitudinal Sentiment Change and Statistical Significance

Cohort	Platform	Δ (M3-M1)	p-value	Reported interpretation
70s-80s	NetEase Cloud Music	+0.6	<0.01	Significant increase (↑↑)
70s-80s	QQ Music	+0.6	<0.05	Significant increase (↑)
70s-80s	TikTok Music	+0.5	<0.05	Significant increase (↑)
90s-00s	NetEase Cloud Music	+0.3	0.12	Significant increase (→)
90s-00s	QQ Music	+0.2	0.25	No significant increase (→)
90s-00s	TikTok Music	+0.3	<0.05	Significant increase (↑)

Note: ↑↑ denotes a strong highly significant increase; ↑ a significant rise; → a non-significant trend

4.3 Platform Architecture and Generational Emotional Rhythm

The three-month results show an interaction between age cohort and platform architecture. Older users benefit most consistently from environments that support continuity, narrative comment practices, and repeated contact with a familiar repertoire. NetEase Cloud Music and QQ Music make prior comments, memories, and stable communities visible, allowing positive affect to accumulate through ritual familiarity. This helps explain the sustained improvement summarized in the original paper as a 23% rise in emotional energy on traditional platforms. The mechanism is not nostalgia in isolation; it is nostalgia renewed through collective recognition.

Younger users follow a different temporal pattern. Their Month 2 decline is followed by partial recovery, but only TikTok Music produces a statistically significant net gain. Its short-form, recommendation-driven environment supplies rapid shifts in content and frequent feedback, which are suited to episodic mood repair. The original analysis expresses this advantage as a 40% improvement in emotional recovery efficiency. Such an environment does not necessarily produce the same durable emotional stock observed among older listeners. Instead, it offers repeated opportunities for quick recalibration. The distinction is between cumulative emotional energy and adaptive emotional rebound.

Comment-system affordances deepen this divergence. Older listeners more often participate asynchronously, using narrative memory and reflective appreciation. Younger listeners are more likely to join synchronized bursts of danmu, emoji, and reply activity. These exchanges create a fast-moving affective arena in which mood can spread and turn over quickly. Popular music therefore performs two social roles at once: it is a ritual archive that preserves intersubjective continuity, and it is a responsive interface for short-cycle emotional regulation. Cohorts emphasize those roles differently because their media habits, symbolic vocabularies, and expectations of interaction differ.

The proposed mechanism can now be stated more precisely. Platform participation provides the interactional occasion; shared songs and discourse focus attention; reciprocal replies and aligned sentiment create emotional resonance; and repeated positive resonance is associated with improved subjective well-being. Age moderates the temporal form of this pathway, while platform design moderates its intensity. For older listeners, the strongest route runs through memory, narrative continuity, and stable recognition. For younger listeners, it runs through immediacy, adaptive recommendation, and high-frequency feedback.

4.4 Limitations and Directions for Causal Research

The observed relations are correlational. Stable personality differences, concurrent life events, socioeconomic position, or wider cultural conditions may influence both platform behavior and emotional expression. The geographic concentration of the sample in more economically developed coastal and central provinces also limits generalization to the entire population of Chinese listeners. In addition, the source manuscript reports several sample counts associated with different stages of recruitment and analysis. Retaining those counts makes the record transparent, but future work should publish a participant-flow diagram and a preregistered rule for inclusion in each analytic subset.

Stronger identification strategies are needed before the music interaction-emotional resonance-well-being sequence can be interpreted causally. A long-duration panel could follow the same accounts and use fixed effects to absorb stable individual heterogeneity. A difference-in-differences design could exploit the introduction of a platform feature as an external shock. Randomized trials could assign participants to different listening and interaction tasks, thereby separating the effect of musical exposure from the effect of visible social response.

The measurement model can also be widened. Audio descriptors would connect interaction patterns to musical structure; biometric or physiological signals could test whether textual recovery corresponds to embodied regulation; and structural equation modeling could separate direct effects from mediated paths. These extensions would strengthen causal validity while preserving the central sociological insight that well-being emerges within a patterned relation among music, symbols, people, and platform affordances.

5 CONCLUSION

This paper reconsiders digital music listening as a sequence of socially organized encounters. Using IRC, platform-specific sentiment measurement, cross-generational comparison, and three-month observation, it shows that the emotional consequences of participation vary by both cohort and technical environment. Older listeners display a steadier accumulation of positive affect in community-oriented, nostalgia-rich settings. Younger listeners fluctuate more sharply, yet algorithmic short-form interaction supports a faster rebound. The contrast is visible in the category distributions, monthly scores, and significance tests, including the older cohort's 82% positive-comment ratio on NetEase Cloud Music and the younger cohort's significant TikTok improvement at $p<0.05$.

The findings refine the proposed pathway from musical interaction to emotional resonance and then to subjective well-being. Music does not supply a uniform emotional benefit. Its social effect depends on whether a platform can match the cohort's ritual tempo: sustained memory and recognition for older users, or rapid and adaptive regulation for younger users. This account extends music sociology into the domain of computationally observable interaction and offers a reproducible basis for future work linking affective computing, platform studies, and emotional sociology.

COMPETING INTERESTS

The author has no relevant financial or non-financial interests to disclose.

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