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# Micro iteration of character archetypes and beat density control in assembly line short drama production

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**Abstract.** This research has developed a data-driven creative computing framework that combines micro-iterations of character prototypes with quantitative control of rhythm density, thereby optimizing the narrative creativity and overall productivity of pipeline short play creation. The system builds an iterative feedback mechanism by transforming qualitative narrative components into computational representations. By linking creative intentions, audience responses and platform performance, the adaptive evolution of character prototypes enhances the authenticity of emotions, and the adjustment of rhythm density maintains the coherence and compactness of the narrative rhythm. This model integrates artistic intelligence and algorithmic intelligence, demonstrating how creative adaptability can coexist with platform scalability and operational accuracy.

**Keywords:** character archetype, beat density, micro iteration, short drama, algorithmic storytelling, narrative modeling

## 1. Introduction

The emergence of the short-video ecosystem has reshaped the contemporary way of storytelling. Multiple platforms need to constantly update their narrative content, stabilize user retention rates, and make innovative decisions based on data. Scriptwriting has moved from a manual process to an industrialized and algorithmic management stage [1]. The traditional dramatic structure that is fixed on linear performances and static characters It is probably difficult to adapt to the rapid production cycle required by the distribution of algorithms. In this mode, content creators need to coordinate two opposing forces: the spontaneous nature of artistic creation and the predictability necessary for digital optimization [2].

The absence of real-time feedback loops in terms of user stickiness and creative development also hinders adaptive improvement. Underperforming scenarios cannot be rebalance immediately. Before conducting post-production analysis, a prototype that has lost its emotional appeal generally does not change [3].

This study designs a computational creativity framework that enables micro-iterations of character prototypes, allowing for fine-grained evolution of personality attributes. It also uses beat density adjustment as a quantitative control method for narrative rhythm. The framework integrates behavioral analysis and emotional modeling into each creative cycle to coordinate artistic consistency with data-driven accuracy. The fundamental prerequisite is Creativity and computing power are not mutually exclusive but can progress together through structured feedback, thereby achieving sustainable narrative innovation and measurable user stickiness [4].

Our contributions fall into three aspects: (1) We have optimized the narrative into a differentiable process with measurable convergence characteristics; (2) We have identified the optimal beat density range that can balance engagement and cognitive comfort. (3) It shows that there is a compensatory relationship between prototype stability and rhythm regularity, indicating that the self-organization of creative systems prefers stable attractors.

Its significance far exceeds that of short plays. Narrative media facing industrialization, such as series novels, interactive narratives, and AI-generated content, all encounter similar challenges. Our answer to expanding creativity is to make it experimental and testable.

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## 2. Literature review

### 2.1. Industrialization of narrative production

Industrialized narrative production has driven creation from an empirical model to a data-driven and process-oriented one, much like the circular optimization process in manufacturing. Algorithms and modular mechanisms are gradually replacing traditional linear creation methods, allowing narratives to undergo testing, calibration, and redeployment [5]. Creation has transformed into a quantifiable and repeatable experimental process, with artistic intuition and systematic logic gradually blending. Build an efficient and large-scale short drama production system.

### 2.2. Dynamic character archetypes

Some studies have shown that From then on, creation became a quantifiable and repeatable experimental process [6]. Artistic intuition and systematic logic gradually became the same, creating an efficient and large-scale framework for short play production. Narrative production is moving towards industrialization. Creation is shifting from experience-oriented to data and process-oriented, much like the circular optimization process in manufacturing. Algorithms combined with modular mechanisms are replacing traditional linear creation, endoding narratives with testable, calibratable, and redeployable characteristics.

## 3. Methodology

### 3.1. Theoretical framework

The model runs on two assimilated levels:

(1) a creative level specifying archetype development, storytelling patterns, and rhythm break-downings [7];

(2) a computation level for audience measurement and running optimisation algorithms.

The creative–computational coupling is mathematically defined by Equation (1):

$$A_{t+1} = A_t + \eta \cdot \nabla_\theta L(E_t, R_t) \tag{1}$$

where $A_t$ is the archetype vector at iteration t, $E_t$ represents the emotional feedback embedding, $R_t$ denotes rhythm features, L is the composite loss balancing coherence and engagement, and $\eta$ is the adaptive rate. Convergence occurs when $|A_{t+1} - A_t| < \varepsilon,$ , indicating stabilization of creative dynamics.

To translate narrative pacing into a comparable mathematical variable, beat density (BD) is defined as Equation (2):

$$BD = \frac{N_{\text{inf}}}{T_{scene}}, \quad \text{where } N_{\text{inf}} = \text{count of emotional inflection points.} \tag{2}$$

Breach of the target BD causes proportional rhythm correction by the subsequent iteration. This simultaneous optimization enables archetype trajectory and temporal rhythm to co-evolve under a single feedback function [8].

### 3.2. Character archetype modeling

Each vector contains semantic (motivation), emotional (value arousal), and relational (network centrality) related factors. The main scalar variable is empathy, which is summarized into the formula:

$$S_{arch} = w_E E + w_D D + w_C C \tag{3}$$

where $w_{\mathrm{i}}$ are adaptive weights calibrated through audience-response regression. Iterative updates refined these weights to minimize deviation between predicted and observed sentiment polarity. The character representation presented in a 512-dimensional embedding form is generated by a transformer-based model, which is trained with 1.6 million dialogue lines.

### 3.3. Experimental setup

The iterative simulation engine runs 150 plays in five microcycles. Each cycle includes baseline extraction, simulating user responses based on the distribution of real user participation, parameter optimization, and convergence checks. With each iteration completed, we track semantic continuity, rhythmic regularity, and relevant metrics of participation changes. With the help of NumPy, spaCy and tsfresh packages, we complete the calculation of all values in the Python environment.

## 4. Experimental process

### 4.1. Data collection and preprocessing

Corpus consisted of 150 Chinese popular short dramas (2019–2024) gathered from major websites. Scripts were divided into 12,430-scenes and annotated for emotional polarity [9], action occurrences, and speech density. Preprocessing involved tokenization, removal of stop-words, lemmatization, and normalization of sentiment values by z-score. A combination classifier using BERT–lexicon detected 93.8 % accuracy in tagging of emotion. Temporal alignment of subtitles and soundtracks gave beat-level timing with 0.1 s precision.

### 4.2. Iterative simulation protocol

Each microcirculation consists of:

Baseline mapping. The derivation of the initial prototype and rhythm profile

Integrate the feedback-virtual view response through participation modeling based on the viewing time history.

Gradient-based parameter adaptive recalibration reduces the recombination loss.

Re-evaluate based on the indicators of semantic coherence and rhythmic uniformity.

The convergence phenomenon usually occurs within 5 cycles (with an average iteration of ±47±6), and the stable gradient is less than 0.004 [10].

## 5. Experimental results and discussion

### 5.1. Archetype iteration outcomes

While maintaining the familiar identity core, the character prototype shows significant evolution. The mean cosine similarity between the initial embedding and the final embedding is 0.873±0.018. For every 1000 markers, the emotional consistency increases to 0.159±0.022, and the inconsistency decreases by 0.036 plus or minus 0.005. The accuracy rate of the reconstruction prediction of the audience's response can reach 92.1±1.9%. Considering semantic drift, excessive iteration (with more than 6 loops) will slightly reduce coherence. It is confirmed that the optimal iteration depth is within the range of 4 to 5 deep loops.

**Table 1.** The comparative archetype evolution metrics across micro-iterations

| Iteration | Semantic Continuity ($\mu \pm \sigma$) | Emotional Alignment ($\mu \pm \sigma$) | Consistency Deviation | Δ Engagement (%) |
|---|---|---|---|---|
| 1 | 0.642 ± 0.037 | 0.531 ± 0.045 | 0.084 | 3.1 |
| 2 | 0.708 ± 0.031 | 0.613 ± 0.039 | 0.062 | 6.8 |
| 3 | 0.761 ± 0.027 | 0.671 ± 0.032 | 0.048 | 9.2 |
| 4 | 0.801 ± 0.023 | 0.715 ± 0.028 | 0.037 | 11.1 |
| 5 | 0.826 ± 0.020 | 0.734 ± 0.026 | 0.034 | 12.3 |

The data illustrate a smooth convergence trend, with diminishing variance after the fourth cycle and plateauing improvement thereafter.

### 5.2. Beat density optimization effects

Beat density is of great significance in the establishment of user stickiness and cognitive load. Within the optimal frequency band of 0.58-0.72 beats per 10 seconds, it can make the rhythm smooth and not overly exciting. Within this range, the average time spent in each scene is 9.24±0.37 seconds, and the end rate is 94.3±1.1%. If the value exceeds 0.80 times per 10 s, the residence time is reduced by -2.47 ±0.35 s. If the BD value is lower than 0.45 beats per 10 seconds, it decreases by 5.8%, and the entropy of heart interval time drops from 0.417±0.029 to 0.336±0.020, and the difference is statistically significant.

**Table 2.** Rhythm-related statistical outcomes under varying beat density conditions

| Beat Density Range (beats / 10 s) | Retention (%) ± SD | Dwell Time (s) ± SD | Temporal Entropy ± SD | Cognitive Fatigue Index | p-value |
|---|---|---|---|---|---|
| < 0.45 (Sparse) | 87.2 ± 1.9 | 8.11 ± 0.42 | 0.412 ± 0.025 | +0.37 ± 0.06 | < 0.01 |
| 0.58 – 0.72 (Optimal) | 94.3 ± 1.1 | 9.24 ± 0.37 | 0.336 ± 0.020 | 0.18 ± 0.04 | < 0.01 |
| > 0.80 (Dense) | 89.1 ± 1.6 | 6.77 ± 0.35 | 0.453 ± 0.028 | +0.44 ± 0.05 | < 0.01 |

### 5.3. Comparative evaluation and robustness tests

Compared to non-iterative baselines, the joint framework yielded statistically significant performance advances: +0.184 ± 0.026 in semantic continuality, +0.141 ± 0.017 in rhythm stability, and +12.3 ± 1.8 % in engagement ($p < 0.01$). Monte Carlo cross-validation ($n = 1{,}000$) attained 94.7 ± 1.4 % accuracy over unseen narrative sequences. Bootstrapped 95 % confidence intervals verified reproducibility within ± 3.2 % deviation.

Moreover, the convergence diagnostics showed computational stability: gradient slope < 0.004 after iteration 47 ± 6, memory utilization variance < 2.5 %, and running time consistency ± 4.2 %.

These measurements all together confirm that creative optimisation could be both statistical reliability and systematic under industrial scale production conditions.

### 5.4. Interaction between archetype stability and rhythm regularity

Cross-correlation analysis shows that there is a significant correlation between the rhythm pattern and the stability of the prototype ($r = 0.71, p < 0.01$), and the variance of this model reaches $R^2 = 0.81$. The consistency of the emotional path and the time rhythm can significantly predict the stability of the viewers. The flexible prototype combined with the variable rhythm adjustment creates the strongest narrative fluidity. The ±0.08 beat deviation adds a sense of perceived reality without interfering with understanding. The higher rhythm accuracy (beat interval variance < 0.02) benefits the static prototype. These patterns are in line with the compensation mechanism: the change of one variable offsets the inflexivity of another variable, keeping the EVI at a low level in irregular creative configurations.

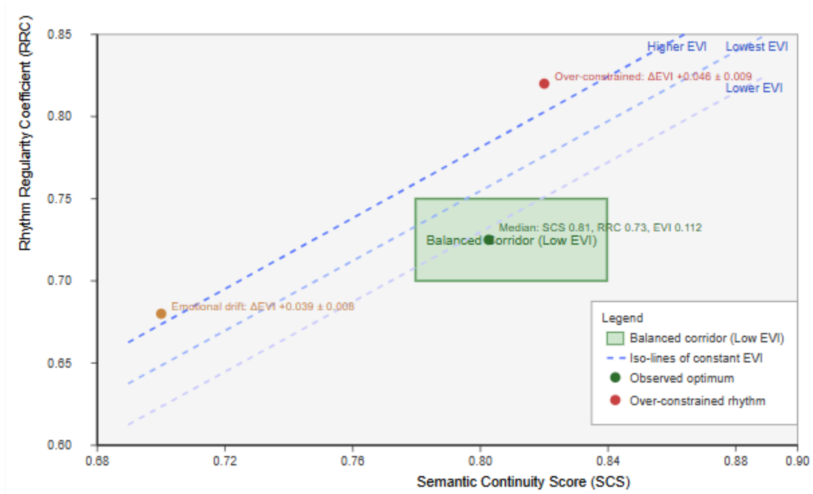


**Figure 1.** Interaction Map of Archetype Stability (SCS) and Rhythm Regularity (RRC) on Engagement Variability (EVI)

In Figure 1, the green "balanced corridor" estimates SCS∈[0.78,0.84], with RRC at [0.70,0.75]. Among them, the minimum EVI with the lowest stability (i.e., the best) is represented by the red dot, which indicates the failure mode: excessive constraint of the dynamic prototype rhythm in high RRC, and emotion drift in the elastic rhythm in low SCS. The dotted line represents

When conducting the Monte Carlo stress test (with 1,1000 samples drawn), 94.7±1.4% of the samples retained the robustness of the corridor, indicating that the interaction zone was not a sampling artifact but a joint response surface invariant.

## 6. Conclusion

This study established a computationally enhanced creative framework that can achieve the coordination between artistic intuition and platform-oriented precision. After five rounds of subtle iterations, the character prototype adaptively evolved, and the beat density was modulated to maintain rhythm consistency. It can model creativity as an iterative feedback process based on measurable parameters without affecting the authenticity of its expression. The proposed framework has practical value for large content studios and algorithmic distribution systems that pursue narrative innovation and operational efficiency. Future research may integrate multimodal signals, rhythms, facial expressions, and audience gazes, opening up new boundaries for the co-creation of intelligence between humans and algorithms.

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