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Research on AI Agent-Assisted Content Planning and Operational Decision-Making Mechanisms for New Media Accounts

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Abstract

At present, many new media accounts are experiencing slower traffic growth, while their content is also prone to homogenization, and planning, publishing, interaction, and post-campaign review often fail to connect smoothly. This paper discusses how AI Agents can assist account content planning and operational decision-making. It sorts out the operational relationship between the four Agent modules and the three-layer platform architecture, proposes a weighted scoring approach on the content side based on *Rel*, *N*, and *E*, as well as a multi-indicator weighted decision-making and dynamic feedback approach on the operation side, and compares these mechanisms with cases such as Fengmang Media, *Z* Vision, and listener interaction. The study argues that Agents can connect scattered operational links and improve the efficiency of standardized task processing. However, existing practices mostly remain at the level of partial application; hot-topic responsiveness and end-to-end collaboration are still insufficient, and human review must be retained for major content and public opinion handling.

Keywords

AI Agent, New Media Operation, Content Planning, Decision-Making Mechanism, Human-Machine Collaboration

1. Introduction

The widespread adoption of generative artificial intelligence is changing the landscape of content production and dissemination in the news and publishing industry. The focus of media organizations has also shifted from simply "making content" to an integrated operation of "production-distribution-interaction-deci-

sion-making" (Lu, 2023). Large models have become relatively adept at drafting articles and answering questions, but once long-term memory, cross-platform coordination, and overall account-level coordination are involved, relying on the model itself is often insufficient. Content planning and operational decision-making remain genuine weaknesses for many teams. OpenAI's five-stage framework comprises chatbots, reasoners, agents, innovators, and organizations (Metz, 2024; see Figure 1). Among them, the "agent" emphasizes active perception, planning, and task completion, which is relatively close to the issues that intelligent operation of new media accounts seeks to address. Overseas industries have already begun exploring large-scale applications of AI Agents ("Owkin to Build AI Agents," 2026). In China, there have been many achievements in development platforms, AIGC applications, safety governance, and ethical regulation, but research specifically discussing how "content planning-operational decision-making" can be collaboratively supported remains relatively limited. This paper intends to sort out the mechanism by which AI Agents provide assistance and to compare it with typical cases, thereby offering a reference for media organizations, brands, and self-media accounts in improving their operational decision-making arrangements.

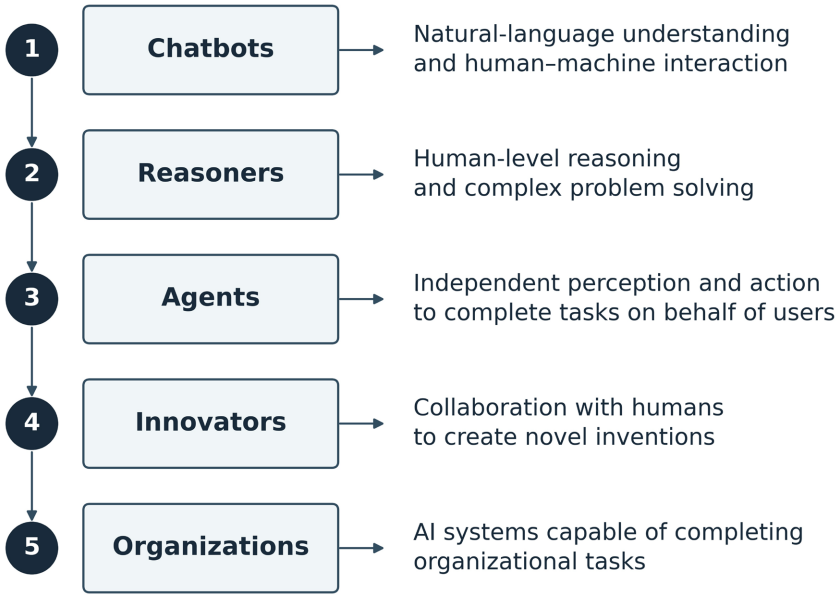


Figure 1. Five stages of artificial general intelligence development. Note. Author-redrawn schematic based on the framework reported by Metz (2024).

2. Integration Mechanism of AI Agents and New Media Operations

2.1. Core Concepts and Technical Pathways

To discuss how AI Agents intervene in the operation of new media accounts, it is necessary to first clarify several concepts that are related to one another but should not be mixed. In this paper, an AI Agent refers to an autonomous system driven

by a large language model and capable of taking action for specific tasks. Its core lies in perceiving the environment, making plans, invoking tools, and completing execution, while the memory module enables continuity between preceding and subsequent tasks. Corresponding to the technical capabilities of the Agent, "content planning for new media accounts" mainly answers what to publish, how to adapt content to different platforms, and when to publish it. "Operational decision-making" by contrast, requires reading communication effects and risk signals, and on this basis adjusting publication arrangements, interaction methods, and resource input. Existing overseas studies provide insights for this type of work from different perspectives: the way LLM-based Agents orchestrate multi-step tasks helps explain how planning and operation can be connected (Nam et al., 2026); the semantic architecture design of domain-specific Agents also provides reference value for knowledge organization and task decomposition in vertical accounts (Ishaq et al., 2026). In China, there are already many Agent development platforms. Wenxin, Coze, Tencent Yuanqi, Dify, Pangu, and others have different emphases in low-code development, knowledge bases, content distribution, and workflow support (see **Table 1**). Differences in platform capabilities determine whether account operation can incorporate content creation, interface invocation, and process control into the same technical pathway.

Table 1. Comparative analysis of mainstream AI agent development platforms in China.

No.	Platform	Main Advantages	Applicable Scenarios
1	Wenxin Agent	Low-code; strong knowledge base	Knowledge Q & A; content creation; customer service
2	Coze	Strong content distribution; rich plugins	Content creation; multi-task operational workflows
3	Tencent Yuanqi	Social ecosystem; low-code	WeChat ecosystem accounts; customer service
4	Dify	Open source; rapid deployment	Building intelligent assistants and content generation tools
5	Pangu Framework	Enterprise-level; high performance	Large-scale data and scenarios with high security requirements

Note. Data from John's Blog (n.d.).

2.2. Pain Points in New Media Operations

From the perspective of tool evolution, the operation of new media accounts has roughly gone through stages such as manual dominance, tool assistance, AIGC participation in creation, and Agent intervention in scheduling. Efficiency has gradually improved, but the problem of connecting different operational links has not been alleviated simultaneously (Ju et al., 2024). In practice, difficulties often appear in a chain-like distribution: on the content production side, the same topic has to be rewritten into versions for multiple platforms, which creates a heavy

workload, and batch generation is also likely to produce content with similar tones and insufficient recognizability; on the distribution and daily operation side, whether the publishing time is appropriate, whether comments can be responded to promptly, and whether different users can be treated differently directly affect account performance, yet many teams still rely heavily on experiential judgment in these links (Xu & Qiu, 2025); at the decision-making level, data from different platforms remain isolated from one another, and it is not easy to clearly identify which content has brought reading, consultation, or conversion; once negative comments or signs of public opinion risks appear, late detection and difficult tracing may also allow small problems to become larger.

2.3. Feasibility of Integration and Agent Framework Mapping

It is precisely against the background of these accumulated pain points that using the basic Agent framework to correspond to account operation has practical significance. As shown in **Figure 2**, an Agent consists of four parts based on a large model: memory, planning, tools, and execution. Among them, memory refers to the account knowledge base and past content; planning refers to specifying topics and publication time; tools refer to connecting with platforms and accessing compliance checking tools; and execution refers to producing content, scheduled sending, interaction, and other actions. Having these modules is still far from enough; an available system is also needed to support account operation.

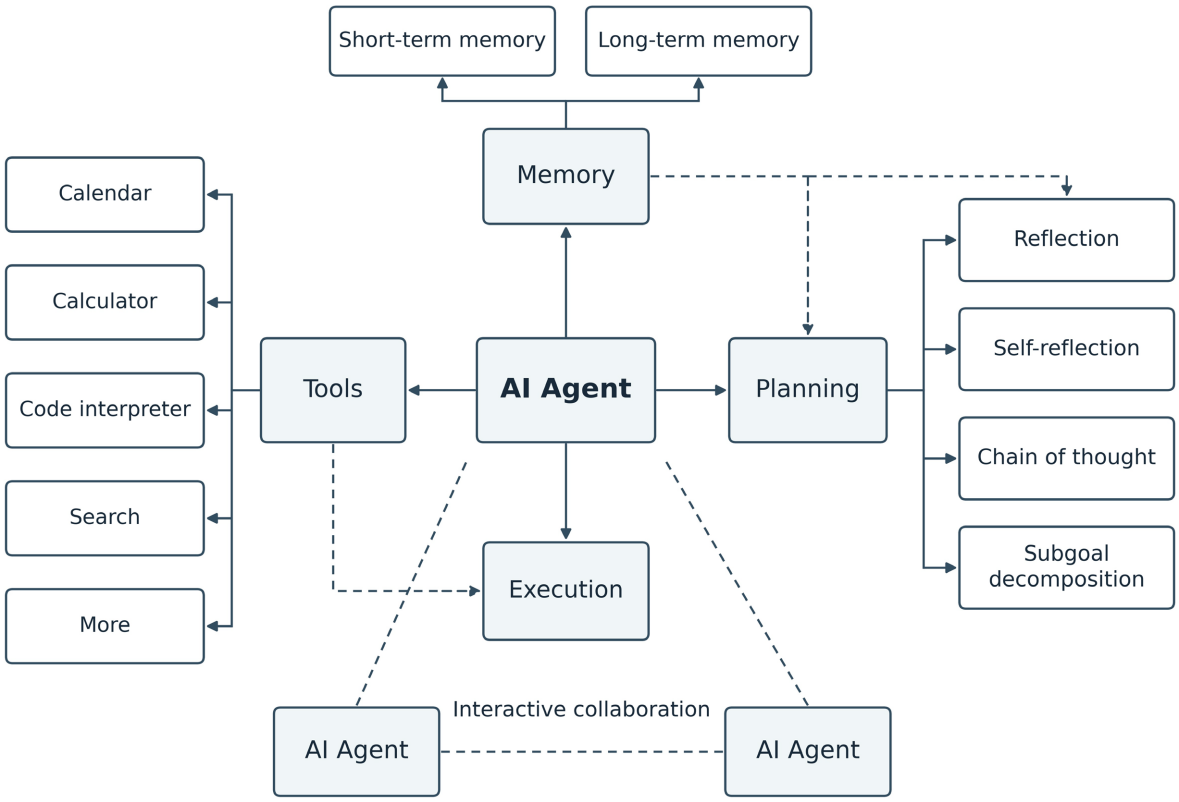


Figure 2. Basic framework of an AI agent. Note. Author-redrawn schematic; conceptual background: Xi et al. (2023).

As shown in Figure 3, AI Agent development platforms usually adopt a three-layer architecture of infrastructure layer-platform layer-application layer. Through the coordinated connection of model management, low-code application development, and third-party interface management tools, they organize hot-topic triggering, content generation, compliance verification, human review, distribution monitoring, effect attribution, and other links into a coherent process (Shen & Su, 2026). Low-code deployment can shorten the application construction cycle and lower the technical threshold, and therefore has certain reference value for new media scenarios that require rapid response to hot topics.

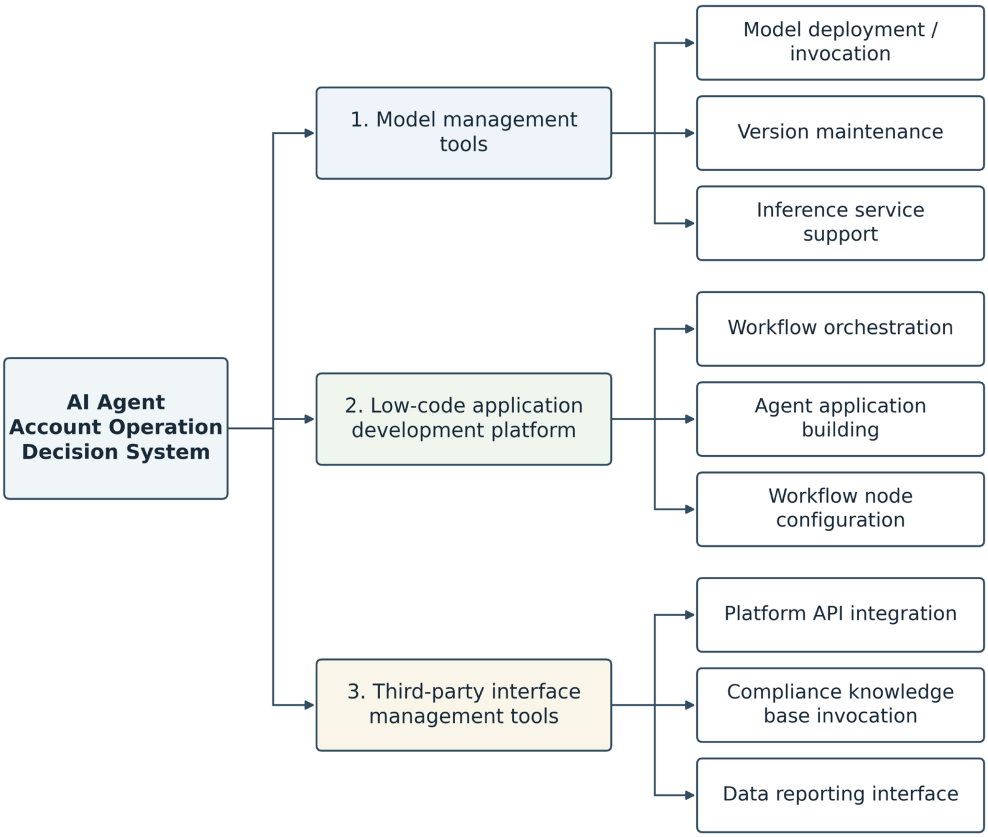


Figure 3. Operational workflow of an AI Agent-based account operation decision-making system (Author-constructed framework).

3. AI Agent-Assisted Content Planning Mechanism

3.1. Reconstruction of the Planning Process

Content planning determines "what the account publishes and in what form it publishes it." It is also the link in which AI Agents intervene first and where deviations are most likely to occur. Planning cannot rely only on temporary inspiration; it also requires stable knowledge support. The platform-layer RAG (retrieval-augmented generation) engine can build an account knowledge base on this basis, incorporating brand specifications, content rules of various platforms, historical drafts, and popular cases into the retrieval scope. This is equivalent to the imple-

mentation of the memory module at the planning end: before the Agent writes a draft, it first checks the knowledge base, so that topic selection and expression will not deviate from the account positioning.

Following hot topics is another demanding task in planning. The planning module usually decomposes this work into several links: monitoring, scoring, triggering, and generation. It first judges whether the topic trend is compatible with the account positioning, and then starts the writing process after the standard is met, thereby compressing the gap between "discovery-discussion-writing" as much as possible. The way the same hot topic is expressed on different platforms is often not the same, so cross-media adaptation is particularly important: the same theme may need to be rewritten respectively into an image-text-oriented version, a short-video script-oriented version, or a shorter interactive post, so as to match the communication habits of different platforms.

Compliance and creativity are not necessarily opposed here. A compliance Agent can first filter out expressions restricted or prohibited by advertising law, platform-sensitive words, and content that conflicts with brand specifications, so as to block obvious risks before publication. For content involving major topics, value orientation, and creative boundaries, human review should still be retained, forming a collaborative path of "Agent proposal-human gatekeeping-Agent execution." If these layers of mechanisms are absent from the planning link, Agent output may become faster, but decisions may not necessarily become more stable.

3.2. Content Value Evaluation Model

Drafts generated by an Agent sometimes read smoothly but have little relationship with the account, or they may look similar across multiple topics. If there is no screening standard before publication, operators still have to judge each draft manually, and the significance of the Agent at the planning end will be discounted. Therefore, at the mechanism level, this paper introduces a comprehensive content score expression to conduct a preliminary screening of whether the content "can be published":

$$S = \alpha \times Rel + \beta \times N + \gamma \times E$$

In this formula, S represents the comprehensive content score; Rel reflects the degree of fit between the draft and the account positioning and vertical field; N reflects whether the topic and expression provide new information or a new perspective; and E reflects whether the content can stimulate interactions such as comments and reposts. All three items can be given reference scores on a percentage scale: Rel can be judged by comparing the draft with the account's historical popular content and platform rules, N can be assessed against the repetition rate of recent similar topics, and E can be initially estimated based on title expression and emotional intensity. α, β, and γ are weight coefficients and satisfy $\alpha + \beta + \gamma = 1$. If a new account is more concerned with opening up the situation, β may be set slightly higher; after the account enters a stable stage, the corresponding weight of Rel should usually be increased to prevent content from deviating from the ac-

count persona. A reference threshold S_0 may be set (for example, 70 points). Drafts above S_0 enter human re-review, while drafts below S_0 are returned for revision or discarded. It must be noted that the above formula is a reference framework for planning and screening. The weights and thresholds must be adjusted through trial runs with specific accounts, and it is not an exact model obtained from large-sample regression. Its function is to turn "it feels acceptable" into "screen it once according to standards first," and then hand it over to human judgment.

3.3. Planning Output

After scoring and ranking, the Agent should not publish directly. Instead, it can push the top two to three options to operators for selection or fine-tuning. Humans are responsible for more of the "tone-setting" and "gatekeeping." Through simple natural language, operators can adjust the tone or add some popular expressions. In this way, the approach of machine screening followed by final human review reduces part of the workload while still retaining some creative ideas. In matrix-account operation, operators can pay more attention to their own account positioning, values, and other aspects, while allowing the Agent to complete repetitive tasks.

4. AI Agent-Assisted Operational Decision-Making Mechanism

4.1. Identification of Decision-Making Scenarios

After content is published, operational work enters the stage of "reading data, making judgments, and making further adjustments." The distribution link first needs to solve the question of "when to publish." The Agent can arrange publishing time in combination with background activity patterns and, when necessary, adopt scheduled or grayscale publishing. Post-publication interaction also tests decision-making speed. When facing comments and private messages, the system can match different response methods according to user tags. General inquiries can be answered by the Agent through retrieving knowledge-base content, while complaints, misunderstandings, or signs of public opinion risks that may spread should be promptly handed over to humans for processing.

4.2. Multi-Objective Decision Optimization Model

Account operation rarely focuses on only one indicator. If operators only pursue exposure, the traffic gained may be broad but imprecise; if they only focus on conversion, it may be difficult for the account to open up the situation. In actual operations, operators often have to make trade-offs among views, interaction, and conversion. This paper uses the following formula to synthesize several types of indicators into a reference value that is convenient for comparison:

$$U = w_1 \times T' + w_2 \times I' + w_3 \times C'$$

U is the reference value of comprehensive operational benefit; T', I', and C' represent the standardized exposure, interaction, and conversion indicators, respec-

tively. Since the original data have different dimensions, direct addition is not comparable. Range standardization may first be conducted within the same statistical period; for example, $T' = (T - T_{\min})/(T_{\max} - T_{\min})$, and the same method applies to I' and C' before they are substituted into the above formula. w_1, w_2, and w_3 are weights, and $w_1 + w_2 + w_3 = 1$. A common setting for brand accounts is $w_1 = 0.5$, $w_2 = 0.3$, and $w_3 = 0.2$; for sales-oriented accounts, w_3 may be increased to around 0.5. What is provided here is a multi-indicator weighted decision-making idea, not a strict multi-objective optimization model with constraints and a solution algorithm. The weights are set by operators according to the stage of the account, while the Agent is responsible for calculating and prompting according to the rules; it should not be understood as replacing human judgment of operational goals.

4.3. Dynamic Feedback Mechanism

The platform environment and user tastes change, so weights that were effective last week may not still be suitable this week. After each round of publication, the Agent can read changes in U and make small adjustments to the weights. For example, if views rise significantly during a certain period while conversion barely changes, w_1 may be reduced by 0.05 - 0.10, and the corresponding magnitude can be added to w_3 so that subsequent decisions are more oriented toward conversion improvement. The adjustment effect can be observed using the following formula:

$$\eta = \left(\left(U_{\text{new}} - U_{\text{old}} \right) / U_{\text{old}} \right) \times 100\%$$

η represents the rate of change in the reference value of comprehensive benefit between two evaluation periods. U_{new} and U_{old} correspond to the new value after adjustment and the old value before adjustment, respectively. If η remains below expectations for two consecutive periods, it indicates that adjusting the weights alone is no longer sufficient, and the reasons should be sought from topic selection or the content structure itself. Repetitive parameter calculation, periodic summarization, and abnormality alerts are suitable for being handed over to the Agent. However, matters involving value judgment, major public opinion events, and final approval for publication must still be handled by humans (Guo et al., 2026). For the mechanism to operate, the key does not lie in how complex the formula itself is, but in "who makes the final decision after the calculation, and who takes responsibility when something goes wrong".

5. Typical Case Analysis

5.1. Application Verification of the Content Planning Mechanism

Media organizations such as Fengmang Media have already applied AIGC to copywriting, painting, video, and other forms of content production, and have made clear progress in cross-media adaptation and content production capacity (Xu, 2024). To a certain extent, this also verifies the functions of the planning and execution components discussed above: if an institution can produce various types

of works in a very short period, it shows that the planning chain from monitoring to generation and then to matching is feasible. However, this still leans more toward the application of AIGC tools. It does not fully reflect elements such as the RAG knowledge base, the hot-topic response closed loop, or Agent workflow orchestration, and overall it cannot yet be regarded as a relatively complete Agent-based collaborative planning process.

5.2. Application Verification of the Operational Decision-Making Mechanism

For AIGC applications, the Z Vision platform has established mechanisms such as multimodal traceability review and privacy compliance monitoring, moving risk handling forward into the content circulation process (Zhu et al., 2026). This corresponds to the "review" link mentioned earlier in risk decision-making and human-machine collaboration. The Inner Mongolia listener interaction communication system, meanwhile, uses AIGC to empower user interaction and layered operation, providing a regional media practice case for interaction decision-making and data feedback (Yue & Li, 2025). These two examples show that to build a sound operational decision-making mechanism, it is necessary both to integrate "safety" into the mechanism and to involve users, while also ensuring that feedback is available afterward.

5.3. Case Comparison and Mechanism Verification

The above cases do not verify the mechanisms proposed earlier to the same degree (see **Table 2**). Fengmang Media mainly supports cross-media adaptation and the execution module in content planning; Z Vision mainly supports risk decision-making and human review; and the listener interaction system mainly supports interaction decision-making and data feedback. Existing practices are still insufficient to cover all links such as hot-topic response, distribution decision-making, and end-to-end Agent platform deployment. This indicates that the mechanism framework proposed in this paper has explanatory power, but its complete implementation still requires further exploration. Practices such as the People's Daily New Media "Four Youthful Styles" planning for the National Two Sessions also show that major themed content still requires humans to take the lead in value orientation.

Table 2. Case comparison and mechanism verification.

Case	Verifiable Mechanism Links	Uncovered/Weak Links
Fengmang Media (Xu, 2024)	Cross-media adaptation; execution module	Knowledge base/RAG; Agent collaborative orchestration
Z Vision (Zhu et al., 2026)	Risk decision-making; human-machine collaborative review	Content planning; distribution/data decision-making
Listener interaction (Yue & Li, 2025)	Interaction decision-making; data feedback	Hot-topic response; risk monitoring

6. Conclusion

Focusing on the problems of "difficulty in topic selection" and "blindness in decision-making" in new media account operation, this paper discusses the mechanism by which AI Agents assist content planning and operational decision-making. The study argues that Agents can connect planning and operation into a relatively complete process through four modules—memory, planning, tool use, and execution—as well as the three-layer architecture of development platforms. On the content side, *Rel*, *N*, and *E* weighted scoring is used for preliminary screening; on the operation side, T', I', and C' are weighted to synthesize a benefit reference value, and η is used to observe the effect of strategy adjustment, while human review and value gatekeeping are retained. As shown by cases such as Fengmang Media, Z Vision, and Inner Mongolia listener interaction, the existence of this mechanism can be demonstrated to a certain extent, but Agent deployment is still not comprehensive enough.

In application, it is necessary to adhere to "human-in-the-loop", retain human review at key nodes, and guide AIGC and Agents toward beneficial applications through a multidimensional ethical framework (Zhang, 2024). At the same time, user data must be used in accordance with laws and regulations to prevent privacy leakage. This study is mainly based on literature and case induction. The formula weights have not yet been empirically calibrated with large samples, and multimodal Agent applications have not been expanded. Future research can be further carried out in areas such as Agent platformization, multi-platform shared knowledge bases, and mechanisms for vertical accounts.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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