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Consumer Decision-Making Mechanisms in Livestream E-Commerce: An Analytical Framework from a Dynamic Evolutionary Perspective

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Abstract. As livestream e-commerce evolves from the "traffic dividend" stage into an era of "stock competition," consumers increasingly display a form of "immunity" to repetitive technological stimuli. Building on a systematic review of the relevant literature, this paper constructs a dynamic symbiotic analytical framework of "technology–demand–consumer behavior." The framework integrates the Stimulus–Organism–Response (SOR) model, parasocial interaction theory, and the technology acceptance and diffusion theories, and further proposes an evolutionary logic of "stimulus–adaptation–restimulus." Within this framework, technological dimensions such as interactivity, immersion, and algorithmic recommendation are paired with consumer demand dimensions including learning-driven, social-driven, and impulse-driven motivations. Together, these dimensions explain the cyclical feedback mechanism between technological evolution and consumer behavioral responses on livestream platforms. To empirically validate the framework, this study employs a structured questionnaire survey and applies structural equation modeling (SEM) to test the hypothesized pathways. The results demonstrate the presence of multi-level mediating effects, showing that technological stimuli significantly shape consumer motivations, which in turn influence behavioral responses. Partial evidence is also found in support of the proposed "stimulus–adaptation–restimulus" logic. These findings not only provide theoretical support for understanding the dynamic evolution of consumer decision-making in livestream e-commerce, but also offer practical implications for platforms aiming to optimize technological strategies and design more adaptive marketing approaches.

Keywords: Livestream E-commerce, Consumer Behavior, Technological Stimuli, Demand Evolution, Dynamic Framework

1. Introduction

Since Mogujie(a fashion platform for young women) first experimented with livestream shopping in 2016 and platforms such as Taobao subsequently launched livestreaming functions, livestream e-commerce has rapidly grown into a major traffic gateway for e-commerce platforms and has become the dominant sales model during large-scale promotional events such as "Double Eleven" [1]. However, the industry is now entering a new stage.

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According to the 2024 China Livestream E-commerce Market Data Report released by the Live E-commerce Working Committee of the China General Chamber of Commerce, the transaction volume of livestream e-commerce reached 53.256 trillion yuan in 2024, an increase of 8.31% year-on-year, but the growth rate showed a marked decline. The market penetration rate was 34.3%, with a growth rate of only 7.52%, also continuing a downward trend. Industry experts argue that this shift marks the transition from a "traffic dividend period" to an "incremental-to-stock competition stage," essentially reflecting a transformation from scale expansion to quality upgrading [2]. At the same time, the report indicates that although the user base grew to 620 million (a 14.81% increase year-on-year), the average annual consumption per capita fell by 0.82% for the first time, revealing that consumers are becoming more rational in their decision-making. Moreover, homogenized content formats have led to "aesthetic fatigue," affecting both viewing duration and purchasing intention [2].

These findings reflect the symbiotic relationship between technological advancement and consumer demand. Technology creates new shopping scenarios for consumers, while consumer expectations and behaviors, in turn, drive the evolution of platforms and marketing models—prompting continuous technological innovation. Livestream e-commerce emerges as the product of this dual dynamic: it is both the result of technological maturity and capital investment, and the natural choice of consumers seeking more intuitive, trustworthy, and efficient shopping experiences. As consumers gradually develop "immunity" to certain marketing tactics, livestream e-commerce faces increasing pressure for transformation and innovation.

Therefore, this study seeks to construct a systematic analytical framework by reviewing existing literature and examining livestream e-commerce from five perspectives: technological platforms, product attributes, live commerce hosts and social factors, consumer heterogeneity, and institutional and environmental influences. Unlike traditional approaches, this paper emphasizes the dynamic evolutionary process of decision-making—namely, how consumer logic is continuously shaped and reshaped within the cyclical interaction of technology, demand, and consumer behavior.

2. Literature review

With the rapid rise of livestream e-commerce, consumer purchase behavior and its underlying psychological mechanisms have increasingly become focal points in academic research. Existing studies approach this topic from multiple perspectives, constructing explanatory frameworks that span technological innovation, product attributes, live commerce host and social factors, consumer heterogeneity, and institutional as well as environmental influences. This section reviews and synthesizes relevant literature to provide the theoretical foundation for the subsequent framework.

2.1. Technological platform perspective

The technological platform is a core differentiator of livestream e-commerce compared to traditional e-commerce. Personalized recommendation systems—by enhancing functional, hedonic, and social value—significantly improve users' perceived value and purchase intention [3]. The integration of AI technologies, including digital live commerce hosts, smart product selection, AI-driven customer service, and virtual scenes, enhances livestream efficiency and interactivity, shifting consumers from "passive viewing" to "active participation" [1]. Based on the SOR theory, interactive tools such as bullet comments and "likes" serve as external stimuli that influence consumer emotions and cognition, ultimately shaping purchase intention [4].

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2.2. Product attributes perspective

Products, as the focal point of purchase decisions, strongly influence consumer intentions depending on their attributes and fit with livestream formats. Key determinants of perceived value include product quality, value, comparability, utility, and presentation [5]. Additionally, product quality, brand reputation, and review credibility have been shown to directly impact consumer purchase intention, with perceived value serving as a mediating factor [6].

2.3. Live commerce host and social factors perspective

Live commerce hosts act as vital intermediaries between platforms and consumers, with their interaction skills and personal traits shown to significantly influence trust and emotional identification. Interaction style, expertise, and personality traits of live commerce hosts substantially shape purchase decisions in livestream shopping [5]. From the perspective of virtual idols, anthropomorphized virtual live commerce hosts have been found to reinforce parasocial interaction, enhancing immersion and stickiness, thereby fostering “socially driven consumption” [7].

2.4. Consumer heterogeneity perspective

Consumers are not a homogeneous group, and their purchasing behavior is shaped by individual differences. Factors such as age, gender, and education have been found to influence purchase intention [8]. Consumer preferences often reflect long-term goals but can be triggered by short-term emotional stimuli [9]. Generation Z emphasizes instant gratification, immersive experiences, psychological compensation, and self-expression [10]. Moreover, different short-video platforms target distinct consumer groups, requiring alignment between product types, audiences, and platforms. Consumer focus also varies across stages of the shopping process, necessitating tailored strategies [11]. However, most existing studies rely on cross-sectional designs and lack dynamic analyses of behavioral change.

2.5. Institutional and environmental perspective

The institutional environment provides foundational support for livestream e-commerce. The Draft Measures for the Supervision of Livestream E-commerce proposes stricter regulation of platform qualifications, live commerce hosts, and service providers [12]. Technology has been argued to deliver inclusive benefits only when supported by institutions, public policy, and social organizations [13]. Successive central government documents have consistently highlighted rural e-commerce, underscoring its role in poverty alleviation and agricultural modernization [14]. Overall, institutional research has largely focused on the macro-level, with insufficient integration into consumer-level micro-behavioral mechanisms.

2.6. Summary and research gaps

To summarize, prior studies on livestream e-commerce consumer behavior have developed diverse perspectives: (1) Technology-focused research underscores how platform functions and interactivity shape user experiences; (2) Product-focused research reveals the importance of quality, category, and marketing fit; (3) Live commerce host and social research highlights personality traits, parasocial interactions, and community-building; (4) Consumer heterogeneity studies reflect the

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diversity of psychological structures and behavioral responses; and (5) Institutional studies call for regulation, policy support, and governance improvements.

Nevertheless, several gaps remain: (1) limited cross-perspective integration makes it difficult to uncover interconnections among variables; (2) insufficient attention to dynamic evolution mechanisms, particularly the "immunity effect" of consumers and the adaptive responses of technology; and (3) weak linkage between macro-level institutions and micro-level behaviors, with little theoretical integration across levels.

Accordingly, this study proposes a "technology–demand dynamic symbiosis" framework to analyze the feedback loops and evolutionary mechanisms of livestream e-commerce, offering a dynamic and systematic theoretical lens for future research.

3. Theoretical framework and research hypotheses

3.1. Framework construction and theoretical foundations

Based on the preceding literature review, this study proposes a consumer behavior analysis framework centered on the dynamic symbiosis of technology, demand, and behavior. Unlike traditional static approaches, the framework emphasizes the interactive feedback loop between platform technologies and consumer needs. Drawing on the biological logic of symbiosis–immunity, it introduces a dynamic evolutionary path of stimulus–adaptation–restimulation to reveal the underlying mechanisms of consumer decision-making in livestream e-commerce contexts.

This framework integrates multiple theoretical foundations. First, the SOR theory highlights how external stimuli influence behavior through cognitive and emotional responses, aligning closely with the structure of technological stimulus–consumer demand–behavioral response. Second, parasocial interaction theory suggests that users establish quasi-social relationships with streamers, strengthening emotional attachment and trust, thereby driving consumption decisions. Third, the technology acceptance model (TAM) and technology adaptability theory explain how users accept or develop immunity to new technologies, supporting the logic of technological iteration–demand adaptation. Finally, diffusion of innovations theory illuminates the processes and patterns of adopting new technologies, helping to explain how livestream e-commerce technologies evolve from early adoption to mass adoption.

In summary, the proposed framework emphasizes the dynamic interaction among technology, demand, and behavior, providing a solid theoretical basis for the subsequent empirical analysis.

3.2. Hypothesis development

In terms of the technological dimension, this study identifies four key elements of livestream e-commerce: interactivity, immersion, algorithmic recommendation, and cross-platform integration. These elements not only construct an immersive shopping experience but also provide external conditions for the activation of consumer motivation.

In the demand dimension, three typical types of consumer motivation are recognized: learning-oriented (rational information acquisition), social-oriented (identity recognition and interaction), and impulse-oriented (emotion-driven and instant purchase). These motivations often coexist and are continuously reshaped as users adapt and platform technologies evolve.

The interaction between technology and demand demonstrates a dynamic symbiotic logic. At the initial stage, new technological means (e.g., virtual live commerce hosts, personalized recommendations) serve as external stimuli to activate consumer motivations. As users adapt,

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certain methods lose effectiveness, leading to “consumer immunity.” Platforms then reconstruct stimuli through algorithmic optimization or new technologies, reactivating consumer motivations. This forms a dynamic closed loop of “stimulus–adaptation–reconstruction.”

Based on this framework, the following research hypotheses are proposed and will be tested through a structural equation model (see Figure 1):

• H1: Technological stimuli have a significant positive effect on consumer motivation

• H2: Consumer motivation has a significant positive effect on consumer behavior

• H3: Consumer behavior translates into user feedback.

• H4: User feedback positively influences technology optimization.

• H5: Technology optimization reinforces technological stimuli, forming a closed-loop path.

• H6a–d: Control variables (age, gender, education, income) moderate the paths from “motivation → behavior” and “technology → motivation.”

Accordingly, this study constructs a cyclical path model of “technological stimuli–consumer motivation–behavioral performance–user feedback–technology optimization,” and tests the hypotheses through survey data and structural equation modeling.

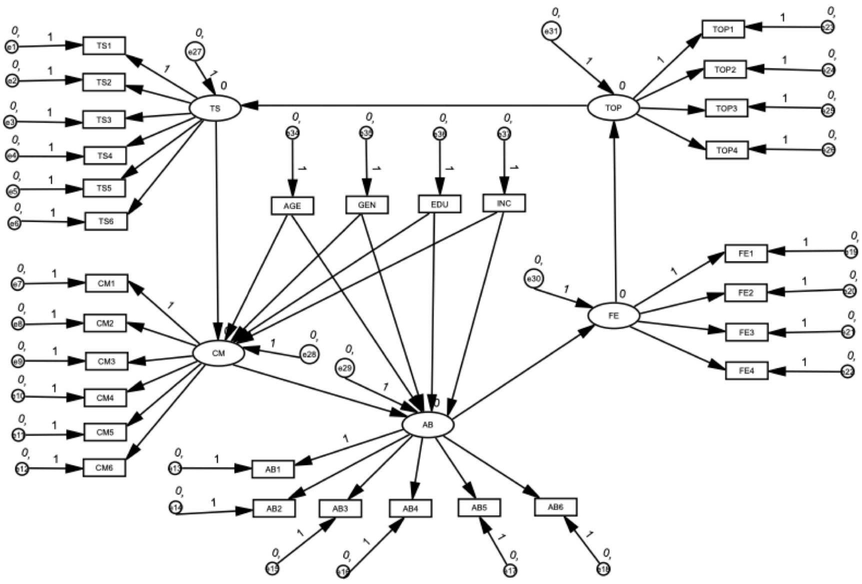

Figure 1. Structural equation model path diagram

4. Empirical analysis and model validation

4.1. Research approach and methods

This study empirically tests the “Technology–Demand–Behavior” dynamic co-evolution model proposed in Chapter 3. It examines the effects of technology stimulus on consumer motivation, the transmission of motivation to behavior, the conversion of behavior into feedback and the impact of feedback on technology perception and optimization, while controlling for gender, age, education, and income.

A cross-sectional online survey was administered using a five-point Likert scale, with five latent variables measured and demographic variables as controls. Screening checks were applied to ensure data quality.

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Data analysis included reliability and validity tests, confirmatory factor analysis (CFA), and structural equation modeling (SEM) to examine hypothesized paths, with mediation and group differences further tested.

4.2. Sample and data sources

This study collected primary data through a questionnaire survey to test the structural paths of the "Technology–Demand–Behavior" dynamic co-evolution framework. The survey was distributed online in April 2025 via platforms such as Wenjuanxing(China's leading online survey & form builder) and disseminated through WeChat groups, QQ groups, and Weibo. Respondents were users with experience in livestream e-commerce, including university students, young professionals, and some freelancers.

To ensure data quality, the questionnaire included a screening item ("Have you ever watched or purchased through livestream shopping?"), a minimum completion time requirement, and checks to exclude inconsistent or invalid responses. A total of 360 questionnaires were returned, of which 327 were valid, yielding an effective response rate of 90.8%. The demographic characteristics of the sample are summarized as follows.

Table 1. Sample characteristics

Variable	Category	Percentage (%)
Gender	Male	40.9
	Female	59.1
Age	18 and below	12.5
	19-25	59.1
	26-35	18.8
	36 and above	9.7
Occupation	University student	62.5
	Enterprise employee	20.5
	Freelancer/Other	17.0
Usage Frequency	≥3 times per week	49.4
	1–2 times per week	35.8
	Occasionally	14.8

Overall, the sample is dominated by young users, with those aged 19–35 accounting for nearly 87%. The proportion of female respondents is higher, and most participants are frequent users of livestream e-commerce. These characteristics are consistent with the typical user profile of this sector.

4.3. Questionnaire design and variable description

To validate the proposed "technology–demand–behavior dynamic co-evolution" framework, a structured questionnaire was designed. It covered control variables (demographic factors), technology stimulus variables, consumer motivation variables, behavioral variables, feedback variables, and technology perception and optimization variables. All items were measured using a

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five-point Likert scale (1 = "strongly disagree," 5 = "strongly agree") to ensure consistency in quantitative analysis.

Table 2. Control variables (demographic factors)

Control Variable	Code	Item
Age	AGE	What is your age? (Options: under 18; 18–25; 26–35; 36–45; above 46)
Gender	GEN	What is your gender? (Options: Male; Female)
Education	EDU	What is your highest level of education? (Options: Junior high school or below; High school/Vocational; Associate degree; Bachelor's degree; Master's degree or above)
Monthly Income	INC	What is your current monthly income? (Options: Below 3000 RMB; 3001–5000 RMB; 5001–8000 RMB; 8001–12000 RMB; Above 12001 RMB)

Table 3. Mapping of latent variables and observed items

Latent Variable	Code	Item
Technological Stimuli (TS)	TS1	Most of the products recommended by the platform match my interests.
	TS2	I am willing to try new brands or products recommended by the platform.
	TS3	The visual effects and background settings during live streaming make me feel realistic and pleasant.
	TS4	When watching live streams, I often lose track of time and become highly focused on the content.
	TS5	Frequent interactions from the streamer during live broadcasts make me feel valued.
	TS6	I prefer streamers or live sessions with strong interactivity.
Consumer Motivation (CM)	CM1	When I see time-limited discounts in live streams, I make purchases immediately.
	CM2	Even when not necessary, I often place orders based on streamers' recommendations.
	CM3	I enjoy participating in live stream interactions such as commenting, liking, and lucky draws.
	CM4	I tend to purchase products when recommended by friends or when watching streams together with them.
	CM5	I use live streams to learn about product functions and usage methods.
	CM6	I believe live streams help me judge more clearly whether a product suits me.

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Behavioral Performance (AB)	AB1	I often make purchases while watching live streams.
	AB2	I purchase through live streams at least once a month.
	AB3	I actively send comments or messages during live streams to interact with the streamer.
	AB4	I frequently participate in voting, lucky draws, or other interactive activities during live streams.
	AB5	I watch live commerce streams at least once a week.
	AB6	I often use live streams to learn about new products or promotional activities.
Feedback Mechanism (FE)	FE1	I feel that the current live-streaming content is repetitive and boring.
	FE2	Compared with before, my interest in live commerce has declined.
	FE3	I increasingly prefer shopping via other channels (e.g., short videos, e-commerce apps).
	FE4	I am no longer interested in live-streaming sessions that I previously enjoyed.
Technology Optimization Perception (TOP)	TOP1	I can sense that the platform's recommendation algorithms are improving, with content becoming more aligned with my needs.
	TOP2	Compared with before, I believe the live-streaming experience is continuously improving (e.g., smoother, more realistic).
	TOP3	I notice that platforms or streamers adjust content or recommendation strategies based on viewer feedback.
	TOP4	I hold a positive view of the platform's ability to enhance user experience through technological means.

4.4. Model construction and validation methods

To verify the applicability of the "Technology–Demand–Behavior" dynamic co-evolution framework, this study constructed a structural equation model (SEM) based on the questionnaire data (see Figure 1 above) and tested the core path relationships. For example, the effect of communication style similarity on purchase intention in live commerce contexts has also been examined using scales and structural equation modeling (SEM) [15].

The model includes five key latent variables—Technological Stimuli (TS), Consumer Motivation (CM), Behavioral Performance (AB), Feedback Mechanism (FE), and Technological Optimization Perception (TOP)—as well as control variables (gender, age, education, and income). The hypothesized causal chain is TS → CM → AB → FE → TOP → TS, forming a dynamic closed loop. Control variables are incorporated to test potential moderating effects on the "motivation–behavior" relationship.

Data analysis was conducted using SPSS Amos 26.0.0 for reliability/validity testing and SEM path modeling. The estimation method was maximum likelihood, and model fit was evaluated using standard indices such as χ^2/df, CFI, TLI, RMSEA, and SRMR.

This methodological approach enables a systematic test of the causal relationships among technological stimuli, consumer motivation, behavioral performance, and feedback mechanisms, and determines whether the closed-loop path holds, thereby validating the theoretical framework proposed in this study.

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4.5. Empirical results

To examine whether the proposed "Technology–Demand–Behavior" dynamic co-evolution mechanism is consistent with empirical reality, this section applies structural equation modeling (SEM) to the survey data, conducting reliability and validity tests, model fit evaluation, and significance testing of the hypothesized paths.

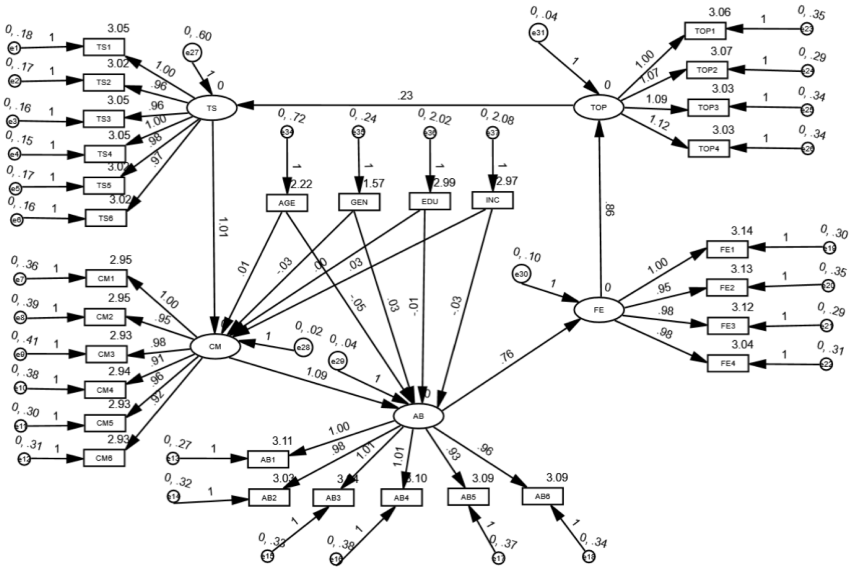

Figure 2. SEM validation results

Descriptive statistics and Pearson correlation analyses were first performed. Results show:

1. All core variables are significantly correlated ($p < 0.001$) in directions consistent with theoretical expectations.

2. Correlation coefficients between TS and CM, as well as between CM and AB, are above 0.6, indicating strong positive associations.

Next, scale reliability and validity were tested. Cronbach's α, CR, AVE were calculated for each latent variable. All Cronbach's α values exceeded 0.83, well above the 0.70 threshold, confirming internal consistency. CR values were all above 0.90, meeting reliability standards. AVE values were greater than 0.69, surpassing the 0.50 benchmark, demonstrating good convergent validity. These results indicate that the scales used in this study possess high reliability and validity.

Table 4. Reliability and validity test results

Latent Variable	Cronbach's α	CR	AVE
TS	1.002 ≈ 1.00	0.968	0.835
CM	0.841	0.934	0.701
AB	0.930	0.954	0.775
FE	0.947	0.907	0.910
TOP	0.830	0.931	0.691

The results indicate that all core variables are significantly correlated ($p < 0.001$), and the directions are consistent with theoretical expectations. The Cronbach's α, CR, and AVE of all latent variables meet the required standards, confirming the good reliability and validity of the scales.

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The structural path analysis results are shown in the following table:

Table 5. Results hypothesis testing results

Hypothesis	Path	Standardized Coefficient	t-value	p-value	Supported
H1	TS→CM	0.985	29.498	< 0.001	Yes
H2	CM→AB	0.976	26.545	< 0.001	Yes
H3	AB→FE	0.906	16.528	< 0.001	Yes
H4	FE→TOP	0.985	22.430	< 0.001	Yes
H5	TOP→TS	0.197	0.420	0.674	No

The findings confirm that technological stimuli significantly shape consumer behavior through motivation, attitudes, and user experience, thereby forming a complete "stimulus–cognition–attitude–experience–intention" chain. This highlights the robustness of the proposed dynamic mechanism. By contrast, the feedback path (TOP → TS) was positive but not statistically significant, implying that feedback effects may be contingent on specific contexts or delayed responses, and thus require further investigation. Moreover, age emerged as a key differentiating factor: younger users exhibited a stronger motivation-to-behavior link, while education, income, and gender showed no significant moderating effects. These results suggest that consumer decision-making in livestream e-commerce is not uniform but varies across demographic groups, particularly in the translation of motivation into behavior. Although the feedback loop was not validated in this study, its theoretical potential underscores the need for broader and longitudinal analyses.

5. Conclusion

This study proposed and empirically tested a dynamic symbiosis framework of "technology–demand–consumer behavior" using 327 valid survey responses. Results show that technological stimuli significantly enhance consumer motivation, which subsequently drives behavior and feedback, forming a transmission chain of "stimulus–motivation–behavior–feedback." The model achieved good fit and strong reliability and validity, though the feedback path from technology optimization to technological stimulus was not significant, indicating possible contextual or time-lag effects.

Despite these contributions, limitations remain: the sample mainly reflects younger users, cultural and behavioral heterogeneity was not fully addressed, and macro-level institutional and technological uncertainties were insufficiently explored. Overall, the study highlights the dynamic nature of consumer decision-making in livestream e-commerce and provides insights for both theoretical understanding and platform strategy optimization.

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