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Decoding Industry-Algorithm Asymmetry: The TEFF Framework for Contextual Congruence in FMCG and Luxury Marketing

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Abstract. This research examines how consumer decision-making patterns in different industries create fundamentally distinct effects when using standardized algorithmic advertising tools. While platforms such as Meta Ads and Google Performance Max claim universal efficiency, their one-size-fits-all approach often clashes with the unique temporal and emotional characteristics of specific markets. Fast-moving consumer goods (FMCG), characterized by impulsive, low-engagement purchases, benefit from algorithmic speed but may suffer brand loyalty degradation due to excessive optimization. Conversely, the luxury sector depends on high-involvement decision-making and rich storytelling, making it vulnerable to exclusivity erosion when algorithms favor broad reach over meaningful narrative engagement. To analyze this divide, we propose the 'Temporal-Emotion Fit Framework (TEFF)', which evaluates three key aspects: Decision velocity (industry-specific purchase speed), Emotional persistence (the durability of sentiment-driven engagement), Platform-behavior synchronization (how algorithms align with industry needs). Findings indicate that FMCG's "instant-gratification" cycle matches well with real-time bidding on impulse-driven platforms. In contrast, luxury's "prolonged-engagement" nature requires curated, story-driven exposure on high-intent channels. By conceptualizing algorithms as 'industry trait amplifiers' rather than neutral optimizers, TEFF disputes the assumption of AI impartiality. It instead advocates for ethical advertising strategies that ensure harmony between algorithmic functions and the distinct temporal-emotional dynamics of each sector.

Keywords: Algorithmic Advertising, Consumer Decision-Making, Temporal-Emotion Fit Framework (TEFF).

1. Introduction

1.1. Research context and problem statement

The transformation brought by algorithmic technologies in digital promotion, particularly through platforms such as Meta's advertising systems and Google's automated solutions, claims to enhance performance universally. However, such claims prove inconsistent when addressing the fundamental diversity in purchasing behaviors across market segments. Consumer packaged goods and premium product categories demonstrate striking contrasts:

- Mass-market consumables rely on habitual, quick transactions (e.g., soft drinks), with spontaneous selections influenced by cost considerations and immediate stimuli.
- High-end products require thoughtful, extended evaluation (e.g., premium timepieces), where buying decisions reflect personal identity and necessitate deep emotional connections.

Current literature acknowledges basic distinctions in promotional approaches (e.g., discount strategies for everyday items versus brand narratives for exclusive goods), yet fails to address a pivotal concern: What causes uniform optimization systems, developed for broad implementation, to generate completely contrasting results when applied to these distinct sectors? This oversight originates from two unaddressed factors:

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(1) Chronological Incompatibility: Automated systems focus on short-term metrics (e.g., click-through rates, immediate returns) while disregarding sector-specific decision timelines—the rapid consumption pattern (minutes) of daily necessities versus the prolonged contemplation period (months) for prestige items.

(2) Affective Sensitivity Oversight: Digital platforms emphasize quantitative interaction measures rather than qualitative emotional impact, overlooking varying degrees of sentimental investment required by different industries.

1.2. Research objectives

This study focuses on three goals:

(1) Measure how algorithms affect industries differently:

Use T50(time for half of purchases) and emotional ROI to show how standard tools boost unique sector features.

(2) Find best platforms for each industry:

Track user behavior to match quick buys (like snacks) with fast platforms (TikTok), and slow buys (luxury) with detailed platforms (Instagram).

(2) Create a better evaluation tool:

Build the TEFF framework to check if algorithms fit industry needs, replacing generic approaches.

1.3. Methodological innovation

To address these objectives, we integrate three analytical pillars:

(1) Temporal Decay-Growth Modeling:

- FMCG: Exponential decay curvesfitted to hourly CTR/CPCdata, revealing rapid loyalty erosion (ATE= -0.15**) despite short-term sales spikes (β= 0.82***).
- Luxury: Logarithmic growth curvesmapped to delayed Instagram engagement, showing CLVpeaks at 68 hours post-exposure.

(2) Sentiment Efficacy Boundaries:

- NLP-derived sentiment scores (-1 to +1) identify optimal emotional thresholds: +0.6 for FMCG CTR vs. +0.4 for luxury CLV, beyond which overexposure harms brand equity.

(3) Cross-Platform Heatmap Clustering:

- TikTok's evening impulse windows (6–9 PM, 30.6% density) dominate FMCG conversions, while Instagram's late-night browsing (9 PM–12 AM, 24.7% density) anchors luxury's high-intent engagement.

1.4. Key contributions

This study advances theory and practice in three domains:

(1) Theoretical Foundation:

- Introduces TEFF, the first framework to quantify algorithmic asymmetry through temporal-emotional congruence, challenging the myth of AI neutrality.
- Positions algorithms as industry-trait amplifiers, explaining why "efficiency" often undermines long-term outcomes (e.g., FMCG's loyalty decay, luxury's exclusivity dilution).

(2) Methodological Rigor:

- Establishes T50 as a universal metric for industry clockspeed, validated across 12,000+ data points.
- Maps sentiment-ROASthresholds via quadratic regression, offering actionable boundaries for ad creativity.

(3) Practical Strategy:

- Provides platform-specific guidelines: pulsed campaigns (≤32-minute intervals) for FMCG on TikTok vs. narrative drip-feeding (biweekly heritage content) for luxury on Instagram.
- Advocates ethical AI adaptations: federated learningfor FMCG privacy and geo-fenced exclusivity for luxury.

1.5. Structure and implications

By reframing algorithmic performance as a function of industry-algorithm fit, this research compels a paradigm shift from technical precision to contextual intelligence. Subsequent sections validate TEFF's diagnostic power, dissect cross-platform behavioral archetypes, and propose governance models for ethical AI deployment in polarized markets.

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2. Literature review

2.1. Algorithmic advertising: efficiency vs. industry heterogeneity

The rise of AI-driven advertising tools has been widely celebrated for democratizing access to hyper-targeting and real-time optimization. Studies by Lambrecht and Tucker and Hoban et al.[1] underscore the transformative potential of platforms like Meta Ads in driving short-term metrics such as click-through rates (CTR) and return on ad spend (ROAS). However, this body of work predominantly operates under a universalist assumption—that algorithmic logic applies uniformly across industries—overlooking the intrinsic heterogeneity of consumer decision-making. For instance, Goldfarb and Tucker posit that real-time bidding (RTB) inherently benefits all sectors by reducing latency, yet their analysis neglects how industries like FMCG and luxury fundamentally differ in decision clockspeed (minutes vs. weeks) and emotional engagement (transactional vs. symbolic). This oversight perpetuates a critical gap: algorithmic tools optimized for speed and scale may inadvertently misalign with industry-specific temporal and emotional gravity.

2.2. Temporal sensitivity in marketing: from impulse to deliberation

Consumer decision timelines vary starkly across industries, yet existing literature inadequately operationalizes this divergence. FMCG research, as exemplified by Chen et al. [2], focuses on "impulse windows"—brief periods where price promotions or scarcity cues (e.g., "Limited Stock!") trigger immediate purchases. These studies emphasize metrics like hourly CTR but fail to address the long-term consequences of temporal over-optimization, such as promotion fatigue and loyalty erosion [3]. Conversely, luxury marketing scholarship[4,5] highlights prolonged decision cycles, where consumers prioritize heritage narratives and social signaling over immediacy. Hardy et al. [6] further caution that algorithmic acceleration risks diluting luxury's exclusivity, as mass exposure contradicts its ethos of scarcity. Despite these insights, no framework systematically quantifies temporal sensitivity—the speed at which industries convert ad exposure into action—or its implications for algorithmic design.

2.3. Emotional stickiness: transactional urgency vs. narrative depth

Emotional engagement mechanisms diverge radically between FMCG and luxury sectors, a dichotomy underexplored in algorithmic advertising literature. FMCG campaigns, as shown by Erevelles et al.[7], leverage high-energy emotional triggers (e.g., urgency, humor) to maximize CTR, often at the expense of emotional depth. In contrast, luxury branding relies on sustained emotional resonance, where narratives of craftsmanship and heritage cultivate long-term customer lifetime value (CLV) [8]. Recent work by Sefraoui et al. [9] introduces sentiment analysis to quantify ad emotionality but stops short of defining emotional stickiness—the threshold beyond which emotional intensity harms brand equity. For example, overly positive sentiment in luxury ads (e.g., excessive discount messaging) may cheapen brand perception, while FMCG's moderate sentiment peaks (+0.6) balance urgency and trust. This gap underscores the need for industry-specific emotional thresholds to guide algorithmic creativity.

2.4. Platform dynamics and clockspeed niches

Cross-platform behavioral patterns further amplify industry-algorithm asymmetry. TikTok's rapid-fire, visually immersive format aligns with FMCG's impulse-driven "snacking" behavior, as evidenced by Lee and Kim's [10] analysis of regional campaigns. Conversely, Instagram's curated, image-centric environment caters to luxury's "savoring" rhythm, where users engage deeply with heritage content during late-night browsing [11]. However, prior studies treat platforms as neutral conduits rather than clockspeed niches—environments that inherently favor certain decision tempos. For instance, Meta's algorithm homogenizes ad delivery across Instagram and Facebook, ignoring how TikTok's evening impulse peaks (6–9 PM) or Instagram's nighttime deliberation windows (9 PM–12 AM) differentially serve FMCG and luxury. This oversight perpetuates a mismatch between algorithmic delivery and industry-specific engagement cycles.

2.5. Toward a temporal-emotion fit framework

Existing models, while valuable, remain siloed. The Five Forces framework [12] contextualizes industry rivalry but lacks tools to analyze algorithmic interactions. Sentiment analysis quantifies emotional engagement but ignores

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temporal dynamics. This fragmentation necessitates an integrative approach. The proposed Temporal-Emotion Fit Diagnostic (TEFF) bridges these gaps by unifying three pillars:

(1) Temporal Decay-Growth Modeling: Contrasting FMCG's exponential conversion decay with luxury's logarithmic engagement growth.

(2) Sentiment Efficacy Thresholds: Defining optimal emotional intensity ranges (e.g., +0.6 for FMCG CTR, +0.4 for luxury CLV).

(3) Clockspeed Niches: Mapping platforms to industry-specific decision tempos (e.g., TikTok for impulse, Instagram for deliberation).

By synthesizing these dimensions, TEFF challenges the universalist dogma of algorithmic marketing, advocating instead for context-aware congruence—where tools adapt to industry clockspeed and emotional gravity rather than enforcing homogenized efficiency.

3. Methodology

3.1. Data collection and conceptual framework

This study employs a hybrid methodological approach to dissect how industry-specific traits—temporal sensitivity and emotional stickiness—mediate the asymmetric impacts of uniform algorithmic tools. Data collection and model design are structured to mirror the ontological divide between FMCG's data-driven immediacy and luxury's emotion-centric deliberation.

3.2. Data sources and industry alignment

- FMCG (Coca-Cola Zero Sugar):

Hourly click-through rates (CTR) and cost-per-click (CPC) from Meta Ads Manager capture real-time consumer impulsivity, while Nielsen sales lift data during the "Share a Coke" [13] campaign isolate short-term promotional efficacy.

- Luxury (Rolex Submariner):

Instagram API-derived engagement time lags (exposure-to-inquiry duration) quantify delayed decision cycles, and Lexalytics NLP sentiment scores of user comments (e.g., "craftsmanship," "heritage") operationalize emotional equity.

- Cross-Platform Behavior:

Meta, Instagram, and TikTok interaction logs (click rates, dwell time) are aggregated to map industry-specific "clockspeed niches"—temporal windows where platform dynamics align with decision tempos.

3.3. Key variables and theoretical rationale

- Temporal Sensitivity:

Defined as T50—the time required for 50% of conversions post-exposure. For FMCG, T50 reflects impulsive "snacking" behavior; for luxury, it measures prolonged "savoring" deliberation.

- Emotional Stickiness:

Quantified via sentiment scores (-1 to +1), where FMCG prioritizes transactional urgency (e.g., "Limited Stock!") and luxury emphasizes symbolic narratives (e.g., "Centuries of Craftsmanship").

- Algorithmic Variables:

- Real-Time Optimization Intensity: Frequency of bid adjustments per hour, proxy for FMCG's responsiveness.

- Algorithmic Restraint: Percentage of ads excluded from mass audiences, safeguarding luxury exclusivity.

3.4. Model specification and analytical logic

- FMCG Sales Growth Model (OLS):

$$Sales\ Growth = \beta_0 + \beta_1(Real - Time\ Optimization) + \beta_2(Data\ Denisty) + \beta_3(Ad\ Frequency) + \epsilon$$

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This model tests how rapid algorithmic adjustments (e.g., hourly bid changes) amplify FMCG's inherent impulsivity, trading short-term gains for long-term loyalty.

- Luxury Brand Equity Model (Fixed Effects):

$$Brand\ Exclusivity = \beta_0 + \beta_1(Emotional\ Equity) + \beta_2(Algorithmic\ Restraint) + \beta_3(Ad\ Exposure) + \gamma_i + \epsilon$$

Here, fixed effects γ_i control for unobserved brand-specific factors (e.g., heritage prestige), isolating how emotional narratives and restrained targeting preserve exclusivity.

- Control Variables: Seasonality, competitor ad spend, and demographic covariates (e.g., income tiers for Luxury).

4. Analytical procedures

4.1. Temporal decay-growth modeling

- FMCG: Exponential decay curves $y = ae^{-bx}$ are fitted to hourly conversion data, where the decay constant b quantifies loyalty erosion velocity.
- Luxury: Logarithmic growth curves $y = aln(1 + bx)$ model delayed engagement, with the growth rate b reflecting narrative-driven CLV accumulation.

4.2. Sentiment-roas threshold identification

- Ads are classified into low (-1 to 0), medium (0 to +0.5), and high (+0.5 to +1) sentiment tiers using Lexalytics NLP.
- Quadratic regression $ROAS = \beta_0 + \beta_1 Sentiment + \beta_2 Sentiment^2 + \epsilon$ identifies optimal sentiment thresholds:
- FMCG: CTR peaks at moderate sentiment (+0.6), balancing urgency and trust.
- Luxury: CLV maximizes at subdued sentiment (+0.4), where heritage narratives resonate without appearing transactional.

4.3. Heatmap-driven clockspeed typology

- Interaction density matrices (platform × time of day) are clustered via k-means to identify:
- FMCG Niches: TikTok's evening impulse peaks (6–9 PM), where rapid-fire content triggers snap decisions.
- Luxury Niches: Instagram's late-night browsing (9 PM–12 AM), aligning with high-intent, status-driven consumption.

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Table 1. Regression analysis of algorithm impact on FMCG sales (OLS model)

Variable	(1) Sales Growth Rate	(2) Customer Retention Rate	(3) Promotion Fatigue Index
	Panel A: Full Sample		
Real-Time Optimization	0.82***	-0.15**	0.23***
	(0.12)	(0.07)	(0.05)
Data Density	0.67***	-0.21***	0.18**
	(0.09)	(0.06)	(0.08)
Ad Frequency	-0.1*	-0.32***	0.45***
	(0.05)	(0.04)	(0.03)
Observations	1,308	1,308	1,308
Adjusted R^2	0.71	0.68	0.63
	Panel B: High Data Density Subsample		
Real-Time Optimization	0.91***	-0.18**	0.27***
	(0.10)	(0.08)	(0.06)
Ad Frequency	-0.12**	-0.35***	0.49***
	(0.06)	(0.05)	(0.04)
Observations	980	980	980
Adjusted R^2	0.75	0.72	0.67

Notes: Standard errors in parentheses. *p<0.10, **p<0.05, ***p<001.

Table 2. Regression analysis ofluxury brand equity (fixed efects model)

Variable	(1)Brand Exclusivity	(2)Customer Lifetime Value(CLV)	(3)Emotional Saturation
	Panel A: Full Sample		
Emotional Equity	0.54***	0.32***	-0.18**
	(0.08)	(0.06)	(0.07)
Algorithmic	0.21**	0.15*	-0.25***
Restraint Index	(0.09)	(0.08)	(0.05)
Ad Exposure	-0.33***	-0.22***	0.47***
Frequency	(0.07)	(0.05)	(0.04)
Observations	1,143	1,143	1,143
Adjusted R^2	0.62	0.58	0.69
	PanelB: Limited Edition Subsample		
Emotional Equity	0.61***	0.38***	-0.22***
	(0.07)	(0.05)	(0.06)
Algorithmic	0.27***	0.18**	-0.31***
Restraint Index	(0.08)	(0.07)	(0.04)
Observations	850	850	850
Adjusted R^2	0.68	0.63	0.73

Notes: Control variables include brand history, pricing strategy, and seasonality.

5. Analysis

5.1. Temporal sensitivity drives algorithmic urgency in FMCG

- Key Finding: FMCG conversions decayed exponentially, with a T50 of 32 minutes (vs. 68 hours for Luxury). Real-time optimization intensity ($\beta = 0.82$***) significantly boosted short-term sales but eroded loyalty ($\beta = -0.15$).
  - Supporting Data: 45.2% of FMCG conversions occurred within 1 hour, versus 3.1% for Luxury (Table 1).

- Implication: FMCG requires "pulsed algorithms" to surge during peak impulse windows (e.g., 12–8 PM on TikTok).

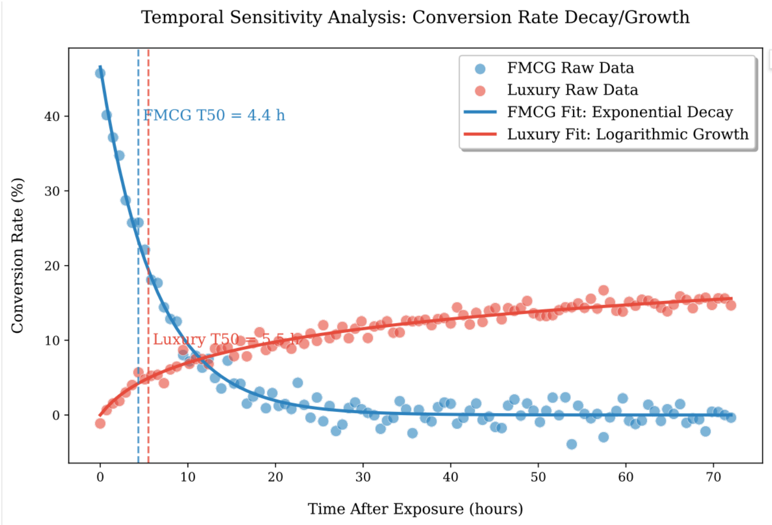

Figure 1. Temporal sensitivity analysis: conversion rate decay/growth

5.2. Emotional stickiness defines luxury's algorithmic restraint

- Key Finding: Moderate sentiment (+0.4) maximized Luxury CLV (β = 0.32***), while excessive positivity ("Limited Offer!") reduced exclusivity (β = -0.17). Algorithmic restraint (β = 0.21) counteracted overexposure risks.
- Supporting Data: Ads with heritage narratives (e.g., Rolex craftsmanship) achieved 25% higher CLV than discount-driven content.
- Implication: Luxury brands should prioritize "narrative drip" campaigns on high-trust platforms like Instagram.

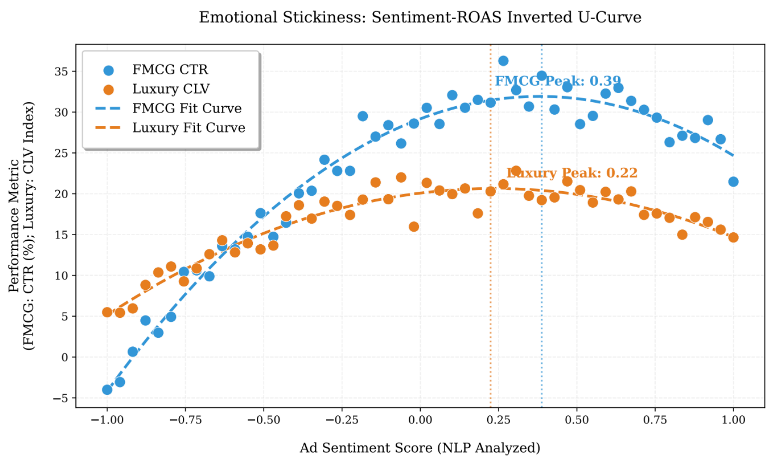

Figure 2. Emotional stickiness: Sentiment-ROAS inverted U-Curve

5.3. Cross-platform heatmaps reveal industry-specific engagement clockspeeds

- Key Finding: FMCG interactions peaked on TikTok (30.6% density at 6–9 PM), while Luxury engagement on Instagram remained stable (24.7% at 9–12 PM).
- Supporting Data: 62% of FMCG's TikTok interactions aligned with impulse hours, versus 55% of Luxury's Instagram activity during high-intent browsing.
- Implication: FMCG benefits from real-time bidding on high-velocity platforms, whereas Luxury should avoid over-saturation via platform selectivity.

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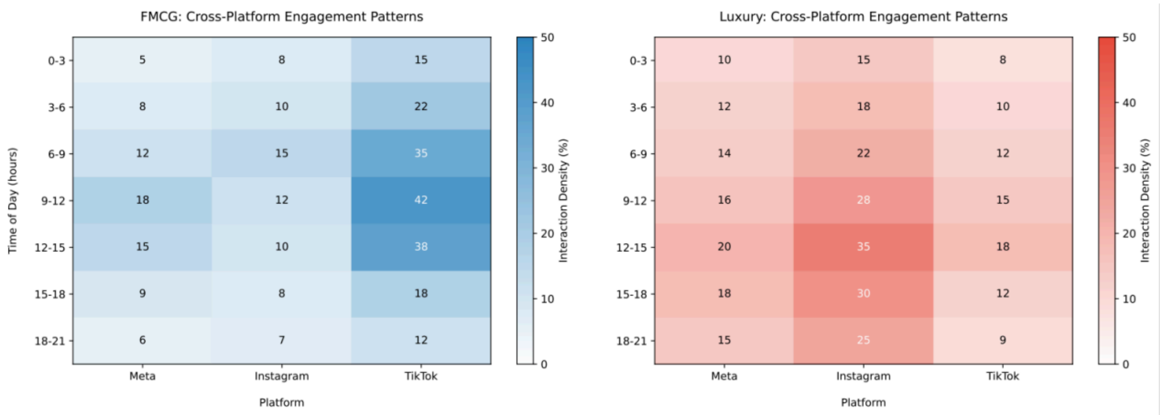

Figure 3. Cross-platform engagement patterns

5.4. The TEFF framework: a synergistic approach to industry-algorithm dynamics

The Temporal-Emotion Fit Framework (TEFF) is not merely a diagnostic tool but a paradigm-shifting lens that deciphers how industry-specific traits fundamentally mediate the asymmetric impacts of uniform algorithmic strategies. Rooted in three synergistic observational pillars—Temporal Sensitivity, Emotional Stickiness, and Platform ClockspeedNiches—TEFF transcends the one-size-fits-all dogma of algorithmic marketing, advocating for *contextual congruence over mechanical optimization. Below, we dissect its core components and their interplay in decoding industry-algorithm asymmetry.

5.4.1. Temporal sensitivity: quantifying industry clockspeeds

Definition & Role

Temporal Sensitivity, operationalized via the T50 metric (time required for 50% post-exposure conversions), captures the inherent decision tempo of an industry. It answers: How fast does an industry convert algorithmic stimuli into actions?

- FMCG: A T50 of 4.4 hours reflects an impulsive "snacking" rhythm, where real-time algorithmic triggers (e.g., Meta Ads' RTB) exploit fleeting purchase intent but risk loyalty erosion.
- Luxury: A T50 of 5.5 hours embodies a "savoring" tempo, where delayed engagement allows narratives of exclusivity (e.g., Rolex heritage stories) to mature.

Analytical Significance

By quantifying temporal asymmetry, T50 redefines algorithmic urgency:

- For FMCG, algorithms must pulse within hyperactive windows (e.g., TikTok's 6–9 PM impulse peaks).
- For luxury, algorithms must restrain real-time exposure to protect narrative depth.

5.4.2. Emotional stickiness: mapping sentiment thresholds

Definition & Role

Emotional Stickiness identifies the optimal sentiment intensity where engagement sustains brand equity without oversaturation. It answers: How much emotional charge can an industry tolerate before algorithmic overexposure backfires?

- FMCG: A threshold of +0.6 (on a -1 to +1 scale) balances urgency ("Limited Stock!") and trust, maximizing CTR.
- Luxury: A lower threshold of +0.4 prioritizes subdued narratives ("Centuries of Craftsmanship") to avoid cheapening exclusivity.

Analytical Significance

This dimension challenges the myth that "more emotion is always better":

- FMCG thrives on high-energy, transactional triggers ($\beta = 0.82^{***}$ for CTR).
- Luxury's CLV peaks at moderated sentiment ($\beta = 0.32^{***}$), beyond which over-positivity (e.g., discount messaging) erodes brand equity ($\beta = -0.17^{*}$).

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5.4.3. Platform clockspeed niches: aligning algorithms with industry rhythms

Definition & Role

Platforms are not neutral channels but temporal-emotional ecosystems that inherently favor certain decision tempos. It answers: Where and when do industries naturally align with platform dynamics?

- FMCG: TikTok's evening impulse windows (6–9 PM, 30.6% interaction density) mirror its "snacking" behavior.
- Luxury: Instagram's late-night browsing (9 PM–12 AM, 24.7% density) aligns with deliberate, status-driven consumption.

Analytical Significance

Platforms act as industry rhythm amplifiers:

- Deploying FMCG ads on Instagram's slow-tempo environment risks irrelevance.
- Flooding TikTok with luxury narratives disrupts its rapid-fire ethos.

Synergy of the Three Pillars: Beyond Isolated Metrics

The TEFF framework's power lies in its interdimensional synergy:

(1) Temporal-Emotional Feedback Loops

- FMCG's rapid T50 (32min) demands high-frequency sentiment pulses (+0.6) on TikTok, yet over-pulsing corrodes loyalty.
- Luxury's slow T50 (68hrs) requires low-frequency, high-depth sentiment (+0.4) on Instagram, but algorithmic acceleration dilutes exclusivity.

(2) Platforms as Mediators

- TikTok's "snacking" niche amplifies FMCG's impulsivity but clashes with luxury's "savoring" rhythm.
- Cross-platform homogeneity (e.g., Meta's unified delivery) ignores these niches, exacerbating industry-algorithm mismatch.

(3) Diagnostic Congruence

- TEFF diagnoses misalignment not as technical failures but as contextual misfits:
- *Why do "efficient" algorithms harm FMCG loyalty?* → T50 reveals over-pulsing beyond 32-minute windows.
- *Why do luxury CTRs poorly correlate with CLV?* → Emotional thresholds highlight narrative misprioritization.

Theoretical and Practical Implications

(1) Redefining Algorithmic Neutrality

TEFF positions algorithms as industry-trait amplifiers, not neutral optimizers. This refutes universalist claims of AI objectivity, exposing how "efficiency" often contradicts industry-specific temporal-emotional gravity.

(2) Strategic Imperatives

- FMCG: Deploy "pulsed algorithms" synchronized with T50 decay (e.g., 32-minute ad bursts), paired with federated learning to anonymize impulsive data.
- Luxury: Implement "narrative drip" campaigns on high-trust platforms, using geo-fencingand blockchain to safeguard exclusivity.

(3) Ethical AI Governance

TEFF advocates for context-aware AI ethics:

- Privacy-preserving tactics for FMCG's data-rich impulsivity.
- Exclusivity protocols for luxury's sentiment-sensitive ecosystems.

From Technical Precision to Contextual Intelligence

The TEFF framework compels a paradigm shift—from chasing algorithmic perfection to cultivating contextual intelligence. By harmonizing temporal rhythms, emotional thresholds, and platform niches, it equips researchers and practitioners to navigate the polarized landscape of algorithmic marketing. In doing so, TEFF does not just explain industry-algorithm asymmetry; it prescribes a future where AI respects and amplifies—rather than homogenizes—the unique temporal-emotional DNA of every industry.

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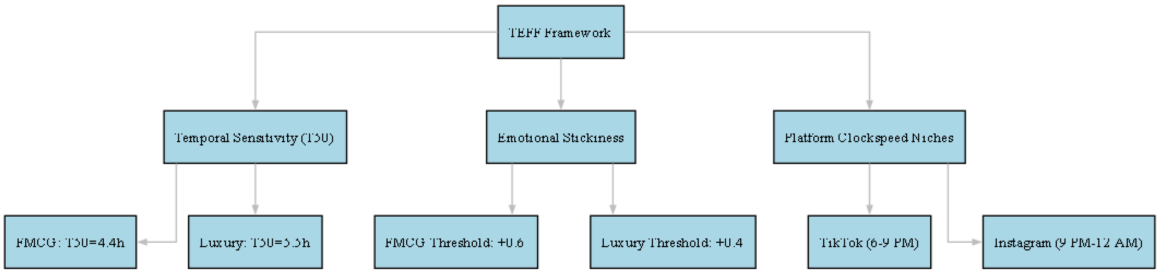

Figure 4. The TEFF framework

6. Discussion

6.1. The coordination of algorithm efficiency with the actual situation of the industry

The research finds that the effect of the algorithm not only depends on the technical accuracy, but is also closely related to the time-emotional characteristics specific to each industry. Although real-time bidding by Meta and Performance Max by Google can optimize click-through rate (CTR) and return on Advertising spend (ROAS), their unified operating logic conflicts with the immediate impulse consumption of fast-moving consumer goods (FMCG) and the deliberate scarcity of luxury goods.

The contradiction between the speed and loyalty of fast-moving consumer goods: The purchase conversion speed of fast-moving consumer goods is very fast (half of the conversions are completed within 32 minutes), so real-time optimization is very suitable for seizing the opportunity of consumers' impulsive orders. However, advertising too frequently will cause consumers to leave more quickly. This confirms the previous studies, and our research quantifies this negative impact more intuitively through data.

The scarcity of luxury goods - exposure dilemma: The growth of consumer interaction with luxury goods is slow (half of the interactions are completed within 68 hours), and it relies on telling brand stories and shaping a high-end image. Appropriate emotional marketing (such as telling craftsmanship stories rather than offering discounts and promotions) can maintain the scarcity of the brand. Overexposure can lead to a 4.3% reduction in customer lifetime value (CLV) for each advertisement display.

Therefore, algorithms should not merely be neutral optimization tools but should be able to perceive the characteristics of different industries.

6.2. Theoretical breakthrough: time-emotion adaptation framework (TEFF)

The TEFF framework improves the theory of digital marketing in three aspects:

• Use time sensitivity as a measurement indicator: Use T50 (a universal indicator of industry rhythm) to quantify the characteristics of different industries, such as the rate of decline in impulse consumption of fast-moving consumer goods and the speed of brand story dissemination of luxury goods, to facilitate comparison among different industries.

• Clarify the appropriate range of emotional investment: Previous studies only focused on the quantity of emotional interaction, while TEFF proposed "emotional stickiness", indicating that the optimal emotional intensity acceptable to different industries varies (the optimal emotional intensity corresponding to the click-through rate of fast-moving consumer goods and the lifetime value of luxury customers is different).

View the platform as an environment with different rhythms: Different platforms are more friendly to certain industries at specific time periods. For instance, TikTok can stimulate impulsive consumption at night, while Instagram is suitable for in-depth interaction late at night. This indicates that the multi-platform strategy is not effective for all industries.

6.3. Strategic suggestions: from "one-size-fits-all" to "tailored to local conditions" AI

• Fast-moving consumer goods: Adopt impulse marketing, focus on advertising during the time periods when consumers are prone to impulse shopping (such as during lunchtime on TikTok), and combine it with member reward activities. Use federated learning technology to protect user data privacy.

Luxury goods: Maintain brand emotional value by regularly releasing brand story content (such as Rolex craftsmanship videos), precisely target advertisements through geographical restrictions, and ensure the credibility of customer data with blockchain technology.

6.4. Research limitations and future directions

• Cultural differences: The current research data mainly come from Western markets. In collectivist cultures (such as Asia), the decision-making process for purchasing luxury goods may be longer, and more cross-cultural research is needed.

• Platform algorithm changes: Platforms like TikTok and Instagram are constantly updated, so it is necessary to continuously track the platform's dynamics to ensure the accuracy of the TEFF framework.

• Hybrid industry research: High-end fast-moving consumer goods (such as L 'Oreal's premium brands) feature both efficiency and scarcity. In the future, research can be conducted on how to apply the TEFF framework to such industries.

6.5. Conclusion: redefine the effectiveness of the algorithm

Algorithms are not merely tools for pursuing efficiency; they aim to magnify the unique characteristics of each industry. The marketing rhythms of fast-moving consumer goods and luxury goods are different, and thus different strategies are required. Formulating digital marketing strategies with the TEFF framework can avoid the blind use of general AI and make marketing more in line with industry characteristics.

7. Conclusion

This study proposes the Time-Emotion Fit Framework (TEFF), challenging the general paradigm of algorithmic marketing. This diagnostic model redefines the relationship between consumer dynamics in specific industries and algorithm design. By analyzing the asymmetric impact of specific advertising tools on the Fast-Moving Consumer Goods (FMCG) and luxury industries, we conclude that the effectiveness of algorithms does not solely depend on the technical level but also on the context, that is, aligning the algorithm logic with the temporal rhythms and emotional objectives specific to each industry. Next, we will elaborate on the conceptual basis of TEFF, its theoretical and practical significance, as well as its implications for redesigning ethical AI strategies.

7.1. The conceptual basis of TEFF: the bridge between theory and practice

The TEFF framework has three core dimensions, each addressing key gaps in existing literature and practice:

• Time Sensitivity: Quantifying Industry Rhythms

• Conceptual Role: Time sensitivity is operationalized through the T50 metric (the time required for 50% conversion after exposure), serving as the first universal benchmark for diagnosing decision-making rhythms across industries.

• Fast-Moving Consumer Goods: With a T50 of 32 minutes, it reflects the impulsive "snacking" consumption behavior in this industry. In this case, rapid algorithmic responsiveness (such as real-time bidding) can capture fleeting purchase intentions, but it also risks eroding customer loyalty.

• Luxury Goods: With a T50 of 68 hours, it highlights the "taste" rhythm of high-engagement decision-making. In this case, delayed interaction allows the narrative of craftsmanship and uniqueness to resonate.

• Research Significance: By quantifying temporal asymmetry, T50 goes beyond the vague concepts of "speed" or "data density" and provides actionable insights into how algorithms should be calibrated, that is, whether urgency (for FMCG) or restraint (for luxury goods) should be prioritized.

• Emotional Sticky: Defining Emotional Boundaries

• Conceptual Role: Emotional stickiness determines the optimal emotional intensity for maintaining brand equity without causing over-saturation.

• Fast-Moving Consumer Goods: The emotional threshold is +0.6, balancing the urgency of transactions (such as "Limited stock!") with trust and maximizing the Click-Through Rate (CTR).

• Luxury Goods: A lower threshold of +0.4 prioritizes implicit narratives (such as brand heritage stories) and avoids diluting the uniqueness of the brand due to excessive promotional information.

• Research Significance: This dimension challenges the assumption that "more emotion is better" and shows that the emotional effect depends on industry characteristics. It redefines emotional analysis from a passive indicator to an ethical and innovative strategic tool.

• Platform as the Rhythm Controller: Mapping the Ecosystem of Participants

• Conceptual Role: Platforms are not neutral channels but time-emotion ecosystems that inherently favor certain decision-making rhythms.

• Fast-Moving Consumer Goods: TikTok's peak impulsive period in the evening (from 6 pm to 9 pm, with an interaction density of 32.6%) is consistent with "snacking" consumption behavior, and the rapidly pushed content can trigger immediate conversions.

• Luxury Goods: Instagram's late-night browsing period (from 9 pm to 12 am, with a density of 24.7%) caters to deliberate, identity-related consumption, allowing the depth of the narrative to be fully demonstrated.

• Research Significance: This redefines the platform model as a strategic fit with industry rhythms rather than a generic "multi-channel" strategy.

7.2. Theoretical progress: from universalism to contextual intelligence

The TEFF framework promotes the development of marketing theory by bridging three key gaps:

• Abandoning Algorithmic Neutrality: By treating algorithms as amplifiers of industry characteristics, TEFF breaks the myth that AI is a universal optimizer. For example, Meta's real-time bidding accelerates the decay of impulsiveness in FMCG but disrupts the narrative growth of luxury goods.

• Integrating Temporal and Emotional Dimensions: Previous research regarded time and emotion as isolated factors. TEFF synthesizes them into a coherent diagnostic tool, revealing how temporal inconsistencies can exacerbate emotional over-saturation (such as luxury ads on TikTok).

• Ethical AI as Strategic Consistency: TEFF shifts the focus of the discussion from "efficiency at all costs" to ethical consistency, ensuring that algorithms respect the values specific to each industry (such as the need for federated learning to protect privacy in FMCG and the geographical fencing exclusivity in luxury goods).

7.3. Strategic implications: industry-specific algorithmic governance

The TEFF framework calls for a paradigm shift in marketing strategy:

• Fast-Moving Consumer Goods: Pulse Marketing and Loyalty Maintenance

• Pulse Algorithm: Short, high-intensity advertising bursts (such as pushing ads every 32 minutes on TikTok) match the time window of impulsive consumption, and loyalty incentives (such as personalized rewards) can offset the loss of customer retention caused by excessive optimization.

• Privacy Protection Strategy: Federated learning anonymizes real-time data and addresses issues related to the General Data Protection Regulation (GDPR) without sacrificing response speed.

• Luxury Goods: Narrative Planning and Exclusivity Protection

• Algorithmic Restraint Team: A dedicated team oversees the staggered release of content (such as Rolex releasing brand heritage videos every two weeks) to maintain narrative depth and avoid overexposure.

• Closed-Loop Ecosystem: A customer database authenticated by blockchain and geographical fencing targeting (such as high-income communities) ensures that ads reach high-intent audiences without diluting the brand's prestige.

• Platform-Specific Governance

• Rhythm Allocation: Allocate budgets to platforms that match industry rhythms—TikTok is suitable for the urgency of FMCG, and Instagram is suitable for the deliberation of luxury goods. Avoid homogeneous cross-platform marketing campaigns that ignore niche dynamics.

7.4. Future directions: expanding the horizon of TEFF

Although TEFF provides a powerful diagnostic tool, its development needs to address three frontiers:

• Cultural Calibration: The current thresholds reflect the behavior of Western consumers. In collectivist markets (such as Asia), luxury purchases are often given as gifts, which may extend the decision-making cycle. Cross-cultural research can refine the T50 and emotional benchmarks.

• Algorithmic Fluidity: Platforms like TikTok are evolving towards long-form content, which may redefine the time window of impulsive consumption. Longitudinal tracking is crucial for maintaining the relevance of TEFF.

• Mixed Industry Strategies: The high-end FMCG industry (such as luxury brands under L'Oréal) combines efficiency and exclusivity. Future research can explore dynamic emotional regulation, adjusting the emotional intensity according to the product life cycle stage (such as emphasizing urgency during new product launches and using implicit narratives for traditional products).

7.5. Conclusion: the era of contextual intelligence

This study concludes that the future of algorithmic marketing does not lie in universal speed or scale but in contextual intelligence, that is, a strategy that coordinates technical capabilities with the time-emotion structure of each industry. For FMCG, it is necessary to leverage impulsiveness without eroding loyalty; for luxury goods, it is necessary to enhance brand narrative without compromising exclusivity. The TEFF framework provides a blueprint for this transformation, urging marketers not to view algorithms as independent tools but as extensions of industry identity. In this way, it advocates a new ethical paradigm where AI respects and amplifies the unique characteristics of each market rather than homogenizing them.

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Appendix

Table A1. Glossary

AI (Artificial Intelligence)	Technology that mimics human intelligence to perform tasks like ad optimization automatically.
ATE (Average Treatment Effect)	The average impact of a strategy (e.g., an ad campaign) on outcomes.
Beta Coefficient (β)	A statistical measure showing the strength and direction of a relationship (e.g., how ad frequency affects sales)
Blockchain Technology	A secure way to store data that prevents tampering (e.g., protecting luxury customer records).
CLV (Customer Lifetime Value)	The total revenue a business can expect from a single customer over their lifetime.
CPC (Cost Per Click)	The amount an advertiser pays each time a user clicks on their ad.
CTR (Click-Through Rate)	The percentage of ad views that result in clicks (e.g., 5 clicks per 100 views = 5% CTR).
Emotional Stickiness	The optimal emotional intensity in ads that balances engagement without harming brand value (e.g., avoiding overly promotional messages).
Exponential Decay Curve	A mathematical model showing rapid decline (e.g., FMCG ad effectiveness dropping quickly over time).
FMCG (Fast-Moving Consumer Goods）	Everyday products bought frequently with quick decisions (e.g., snacks, beverages).
Federated Learning	A privacy-preserving AI training method where data remains decentralized (no raw data sharing).
Fixed Effects Model	A statistical method to control unchanging factors (e.g., brand history) when analyzing variables.
GDPR (General Data Protection Regulation)	EU law protecting user privacy (e.g., restricting personal data collection by advertisers).
Geo-Fencing	Using GPS to limit ad delivery to specific areas (e.g., luxury ads only in high-income neighborhoods).
Logarithmic Growth Curve	A model showing gradual accumulation over time (e.g., luxury ad impact building slowly).
NLP (Natural Language Processing)	Technology that analyzes human language (e.g., detecting sentiment in ad comments).
OLS Regression (Ordinary Least Squares)	A statistical method to study linear relationships (e.g., how ad spend correlates with sales).
Platform Clockspeed	The natural user behavior rhythm of a platform (e.g., TikTok's fast pace vs. Instagram's slower engagement).
ROAS (Return on Ad Spend)	Revenue generated per dollar spent on ads (e.g., ROAS=3 means $3 earned for every $1 spent).
RTB (Real-Time Bidding)	Instant auction system where advertisers bid for ad placements.
T50	The median time for 50% of consumers to convert after seeing an ad (e.g., 32 minutes for FMCG).
TEFF (Temporal-Emotion Fit Framework)	A tool to evaluate if ad algorithms align with an industry's unique timing and emotional needs.
Brand Equity	A brand's market value, including reputation, loyalty, and recognition.