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Research Article

Redefining Customer Acquisition Operations: A Predictive CLV Optimization Playbook for Dynamic Marketing Planning

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ABSTRACT

Short-term measures like click-through rates, last touch attribution, and immediate return on ad spend dominate digital paid advertising decision making, hiding consumers' long-term economic value and skewing investment towards low-quality acquisition. The conceptual foundation for a predictive, Customer Lifetime Value (CLV) driven paid advertising optimisation system based on dynamic value signalling and behavioural event tracking is presented in this study. In light of users' changing behavioural trajectories, the framework reframes paid media as a forward-looking capital allocation system that dynamically modifies spend, bidding intensity, creative deployment, and conversion values. It presents a point based journey rating system to categorise acquisition pathways as optimistic or bearish signals of future lifetime value using first-party data from GA4, server-side tracking, CRMs, and CDPs. The framework extends CLV from a retrospective measure into a strategic control logic for paid media decision-making by emphasising cohort-level inference and adaptive organisational sense-making. It was created for privacy-constrained situations.

Keywords: customer lifetime value; paid media strategy; GA4; event tracking; dynamic attribution; marketing technology; privacy regulation; algorithmic decision making

1. INTRODUCTION

These days, digital advertising systems may operate at previously unheard-of levels thanks to real-time bidding, machine learning-based targeting, and algorithmic creative optimization. Nevertheless, short-term performance metrics like clicks, conversions, CPA, and last-touch ROAS remain the cornerstone of paid advertising strategy in spite of these advancements. This creates a structural paradox: decision-making still favours instantaneously observable results even while platforms are equipped to interpret long-term behavioral data. As a result, brands prioritize quick conversion above long-term financial gain. This imbalance has worsened as a result of privacy rules (GDPR, CCPA), signal loss from cookie deprecation and walled gardens, and market maturity, where low acquisition costs increasingly correlate with low-quality clients. Although it offers a theoretically viable alternative, Customer Lifetime Value (CLV) is now primarily used for retrospective analysis rather than real-time media deployment. This paper argues that the primary barrier is not measuring precision but rather strategic orientation. In paid media, attribution-based optimisation must give way to anticipatory optimisation, where spend is guided by projected value trajectories inferred from early behavioural indicators.

2. PROBLEM STATEMENT

The Central Problem: In digital environments with limited privacy, how can a paid media strategy be created as a predictive, CLV driven system that dynamically distributes spend, attribution weight, creative focus, and conversion value depending on users' behavioural journeys rather than static, last-touch conversions?

Sub-Problems Embedded in the System

I. Behavioural Ambiguity: Although early-stage users seldom convert right away, their actions provide indicators of potential future benefits.

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II. Attribution Myopia: Instead of rewarding downstream input, current attribution models emphasise immediacy.
III. Static Conversion Values: Regardless of the results in the future, conversion events are valued equally.
IV. Creative Myopia: Lifetime customer quality and creative optimisation are unrelated.
V. Organizational Fragmentation: Attribution, strategy, media purchasing, and data all exist in separate systems.

3. RESEARCH QUESTION AND OBJECTIVES

Primary Research Question:

How can media allocation, attribution logic, and creative strategy be redefined to maximise long-term profitability across publishers and D2C brands within privacy limitations using a predictive CLV driven paid media optimisation framework based on behavioural event scoring and dynamic value signalling?

Research Objectives:

I. Must think of paid media not as a conversion engine but as a system for allocating value over time.
II. To create a grading system based on behavioural events that forecasts CLV trajectories.
III. To illustrate how dynamic media investment might be guided by optimistic versus negative signals.
IV. To incorporate dynamic conversion values into optimisation and bidding logic.

4. METHODOLOGY

Instead of using empirical estimation, this study uses an interpretive, qualitative research approach based on conceptual synthesis. It is derived from:

I. CLV literature and marketing approach.
II. Research on algorithmic governance and information systems
III. Analysis of privacy regulations and platform economics

The objective is theoretical generalisation, or creating a framework that can be applied to other platforms and sectors.

5. SYSTEM ARCHITECTURE: PAID MEDIA DRIVEN BY BEHAVIOURAL EVENTS

5.1 Data Infrastructure and Tooling

Instead of using identity-level tracking, a CLV driven paid media system uses first-party behavioural indications.

Core Tools & Integrations:

1. GA4/GA Server-Side: monitoring behaviour at the event level
2. Tag Managers: regulated signal flow (GTM, sGTM)
3. Event normalisation using CDPs (Segment, mParticle, RudderStack)
4. CRMs (Salesforce, HubSpot): post-conversion value feedback
5. Cohort study with data warehouses (Snowflake, BigQuery)
6. Value-based bidding on ad platforms (Google Ads, Meta, DV360)

6. MAPPING THE USER JOURNEY AS A POINT BASED VALUE SYSTEM

(From Behavioral Signals to Media Decisions)

6.1 Why a Point System Is Necessary (Conceptual Nuance)

Three structural realities exist in ecosystems where privacy is restricted: At acquisition time, we are unable to observe the entire lifespan value. Causality cannot be clearly attributed. Before results are achieved, we must take action.

Therefore, the objective of a point-based system is decision superiority under uncertainty rather than prediction accuracy. As a proxy governance tool, the point system transforms early, weak behavioural signals into directed confidence that may be put to use.

This is crucial: CLV [1] ≠ number. CLV stands for future economic contribution. Points put that belief into practice.

6.2 System Architecture Overview (High-Level)

Paid Media Touch → GA4 Event → Event Normalization

→ Event Scoring Engine

→ Cumulative Journey Score

→ Cohort Classification (Bullish / Neutral / Bearish)

→ Media, Creative & Value Decisions

This loop runs **continuously**, not post-hoc.

6.3 Step 1: Describe the universe of behavioural events.

6.3.1 Event Selection Principle (Critical Nuance)

Not every event is worthy of a point. Events are only eligible if they meet at least one of the requirements listed below: Depth of signal purpose Indicate the development of habits Align the signal with the brand Signal quality after acquisition Vanity events (page_view, session_start) should be avoided unless they are contextualised.

6.3.2 Example: D2C Apparel Brand – Event Taxonomy

Event Category	GA4 Event	Description
Content Engagement	scroll_75	Scroll ≥75% on brand story page
Product Intent	view_item_multiple	Viewed ≥3 product PDPs
Decision Friction	size_guide_view	Indicates purchase seriousness
Return Behavior	return_visit_48h	Second session within 48h
Purchase Quality	purchase_no_discount	Full-price conversion
Relationship Signal	email_signup_pre_purchase	Voluntary commitment

6.4 Step 2: Give Directional Point Values (Rather Than Weights)

6.4.1 Key Rule (Very Important)

Points are not cardinal; they are ordinal. They are accustomed to:

1. Rank trajectories
2. Examine cohorts
3. Make decisions
4. They are not chances.

6.4.2 First Point Assignment Backtesting

Historical cohorts are used to assign logic points: "Which early events were more common among users who eventually became high LTV?"

Example Initial Scoring Table

Event	Signal Type	Points
First session bounce	Strong negative	−10
Scroll ≥75% (brand page)	Identity alignment	+8
View ≥3 PDPs	Intent depth	+12
Size guide view	Purchase seriousness	+6
Return visit ≤48h	Habit signal	+15
Email signup (pre-purchase)	Relationship intent	+18
Purchase with >30% discount	Low margin / churn risk	−12
Full-price purchase	Value alignment	+20

Negative points are essential
They prevent false optimism.

6.5 Step 3: Temporal Accumulation: The Journey Is More Important Than the Events

6.5.1 Why Time Is a First-Class Variable

If the timing of two users' identical occurrences is different, they are not equal. For instance, User A: 3 PDPs in 10 minutes -> impulse User B: three PDPs over two days → discussion (usually with a higher CLV)

6.5.2 Time-Adjusted Scoring Rule

Introduce **decay or amplification multipliers**:

Behavior	Modifier
Repeat event within 24h	×1.2
Repeat event after 7 days	×0.9
Cross-session behavior	×1.3
Single-session burst	×0.8

This converts static scoring into **trajectory scoring**.

6.6 Step 4: Cumulative Journey Score

Journey Score=∑(Event Points×Time Modifier)

Example User Journey:

Step	Event	Points	Modifier	Net

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1	Scroll ≥75%	+8	×1.0	+8
2	View 3 PDPs	+12	×1.0	+12
3	Return visit in 36h	+15	×1.2	+18
4	Email signup	+18	×1.3	+23
Total				**+61**

6.7 Step 5: Bullish / Neutral / Bearish Classification

6.7.1 Classification Is Relative, Not Absolute

Thresholds are **distribution-based**, not fixed.

Example (weekly recalibrated):

Segment	Score Range
Bullish	Top 25%
Neutral	Middle 50%
Bearish	Bottom 25%

This adapts to:

1. Seasonality
2. Channel mix
3. Creative shifts

6.8 Step 6: Linking Scores to Decisions about Paid Media

6.8.1 Media Buying Rules (Concrete)

Cohort Type	Media Action
Bullish	Increase bids + expand lookalikes
Neutral	Maintain bids, test creative
Bearish	Reduce bids, cap frequency

6.8.2 Dynamic Conversion Value Injection (Google Ads Example)

Instead of:

purchase = ₹1,000

Use:

conversion_value = base_value × (1 + journey_score / 100)

Example:

1. Base purchase value = ₹1,000
2. Journey score = 60

₹1,000×(1+0.6)=₹1,600₹1,000 × (1 + 0.6) = ₹1,600₹1,000×(1+0.6)=₹1,600

Google's value-based bidding now **overbids for high-quality customers automatically**.

6.9 Step 7: Creative Feedback Loop

6.9.1 Creative Is Scored Indirectly

Creative is evaluated by:

1. Average journey score generated
2. % of users entering bullish cohort
3. Retention curves of exposed cohorts

Creative Type	Avg Journey Score	Bullish %
Discount-led	+18	12%
Story-led	+47	38%
Utility-led	+33	26%

→ **Creative optimization shifts from CTR to CLV signal generation**

7. PRACTICAL IMPLEMENTATION OF THE BEHAVIORAL SCORING SYSTEM (FROM IDEA TO PRODUCTION)

7.1 Implementation Philosophy (Critical Before Tools)

Successful execution is governed by three principles:

1. Distinguishing issues Monitoring, scoring, decision-making, and media execution
2. Not deterministic, but probabilistic Confidence is guided by scores rather than truth
3. Human-in-the-loop leadership Humans approve what automation suggests.

This prevents brittle systems.

7.2 Real-World Stack which is Minimal, Scalable, and Privacy-Safe

Core Stack (Example)

Layer	Tool
Client-side events	GA4 + GTM
Server side relay	sGTM / Cloud Functions

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Event normalization	CDP (Segment / RudderStack)
Storage	BigQuery
Scoring engine	SQL + scheduled jobs
Media activation	Google Ads / Meta CAPI
Visualization	Looker / Power BI

You **do not need AI** on Day 1.

7.3 Step-by-Step Implementation

We'll walk through a **D2C subscription brand** example.

STEP 1: Define and Instrument Events (Real GA4 Configuration)

Example Event Schema (GA4) parameters: event_name: view_item item_id, category, cost, and content_group

Custom Event (Intent Depth)

```
event_name: multi_pdp_view

trigger:

- user views ≥3 PDPs within 1 session
```

This event is created **inside GTM**, not GA.

STEP 2: Server-Side Event Sending: Why It Matters

Client-side → sGTM → BigQuery

Benefits:

1. Privacy control
2. Deduplication
3. Value enrichment

Example Enrichment (Server-Side)

```
{
  "event": "multi_pdp_view",
  "traffic_source": "google",
  "campaign_type": "non_brand_search",
  "timestamp": "2026-01-12T10:42:00"
}
```

STEP 3: Normalize Events (CDP Layer)

Different platforms send events differently.

Normalize into One Schema:

Field	Description
user_key	GA user_pseudo_id
event_name	standardized
event_time	UTC
source	paid / organic
campaign_id	if paid

STEP 4: Create the Scoring Table (BigQuery Example)

Static Scoring Table

```
CREATE TABLE event_scores (
  event_name STRING,
  base_score INT
);
```

event_name	base_score
multi_pdp_view	12
size_guide_view	6
return_visit_48h	15
discount_purchase	-12

This table is **editable without code deploys**.

STEP 5: Apply Time Modifiers (SQL Logic)

```
SELECT
  user_key,
  event_name,
  base_score *
CASE
    WHEN time_diff_hours < 48 THEN 1.2
    WHEN time_diff_hours > 168 THEN 0.9
    ELSE 1.0
  END AS adjusted_score
FROM user_events
JOIN event_scores USING(event_name);
```

STEP 6: Generate User-Level Journey Scores

```
SELECT
  user_key,
  SUM(adjusted_score) AS journey_score
FROM scored_events
GROUP BY user_key;
```

This runs **hourly or daily**.

STEP 7: Cohort Classification (Production Rule)

```
SELECT
  user_key,
  journey_score,
  NTILE(4) OVER (ORDER BY journey_score DESC) AS cohort
FROM journey_scores;
```

Cohort	Meaning
1	Bullish
2–3	Neutral
4	Bearish

7.4 Activating Scores in Paid Media (Actual Execution)

Google Ads – Dynamic Conversion Values

Instead of static:

```
purchase_value = order_value
```

Use:

```
enhanced_value = order_value * (1 + journey_score / 100)
```

Send via:

1. GA4 measurement protocol
2. Google Ads API
3. **Example**

User	Order	Score	Value Sent
A	₹2,000	60	₹3,200
B	₹2,000	10	₹2,200

Google now:

1. Bids harder for User A–like cohorts
2. Deprioritizes User B–like traffic

7.5 Creative Routing (Often Ignored, Very Powerful)

Rule-Based Creative Deployment

Journey Score	Creative Type
>50	Brand / Story
20–50	Utility / Proof
<20	Offer / Retargeting

Implementation:

1. Use GA audiences
2. Sync to ad platforms
3. Map to creative sets

7.6 Validation Loop (How You Know It Works)

Holdout Test

1. 10–15% traffic not scored
2. Compare:
    a. 90-day retention
    b. Repeat purchases
    c. Contribution margin

Success ≠ immediate ROAS
Success = **CLV lift**

7.7 Failure Scenarios & Fixes

Problem	Fix
Scores drift	Monthly recalibration
Overfitting	Cap max score
Platform feedback loop	Budget throttles
Team mistrust	Transparent dashboards

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8. MEASURING, VALIDATING, AND OPTIMIZING THE BEHAVIORAL SCORING SYSTEM OVER TIME

8.1 Why Traditional KPIs Are Insufficient

A CLV driven behavioral scoring system is anticipatory by design. Its success cannot be evaluated using the same short-term metrics (ROAS, CPA, last-click conversions) that it explicitly seeks to transcend.

Using only immediate efficiency metrics creates false negatives:

1. High-quality cohorts often convert slower
2. Brand-aligned customers may require more touchpoints
3. Long-run value emerges with delay

Therefore, validation must be multi-horizon, combining short-run directional checks with long-run economic confirmation.

8.2 Short-Run Validation: Directional & Diagnostic Metrics (0–30 Days)

Short-term assessment is more concerned with whether the system is acting rationally than with whether it has "won" money.

8.2.1 Internal Consistency Checks (System Health)

These tests make sure the scoring system is stable and not arbitrary.

Key Questions

1. Are deeper levels of engagement correlated with higher journey scores?
2. Do bullish and bearish cohorts behave differently?

Example Metrics

Metric	Expected Pattern
Avg. sessions/user	Bullish > Neutral > Bearish
Time on site	Bullish highest
Content depth	Bullish indicates more extensive research
Return visit rate (7d)	Bullish significantly higher

Scoring logic, not media, is flawed if certain patterns don't hold.

8.2.2 Signal Separation Test

This determines whether users are meaningfully differentiated by the system.

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$$\text{Signal Lift} = \frac{\text{Metric}_{\text{Bullish}} - \text{Metric}_{\text{Bearish}}}{\text{Metric}_{\text{Bearish}}}$$

Example

1. Bullish 7-day return rate: 32%

2. Bearish 7-day return rate: 14%

3. Lift of the signal = +128%

No lift equals no information, which equals no optimisation power.

8.2.3 Media Feedback Sanity Check

Verify that the platform is reacting to dynamic signals in a suitable manner.

Indicator	Desired Direction
Avg. bid for bullish cohorts	↑
CPMs for high-value audiences	↑ (expected)
CPA volatility	↑ temporarily
Conversion volume	Flat or slight ↓

Short-term instability is **normal and acceptable**.

8.3 Medium-Run Validation: Behavioral & Economic Convergence (30–90 Days)

Here, we examine whether early indicators align with actual economic activity.

8.3.1 Cohort Retention Curves

Plot retention by deciles of travel scores

Expected Shape

1. Bullish cohorts: slower decay
2. Bearish cohorts: steep early decline

The score system's predictive effectiveness is diminished if curves significantly overlap.

8.3.2 Revenue & Margin Per User (Not ROAS)

Examine gross margin per user and revenue per acquired user by cohort.

Cohort	Rev/User (90d)	Margin/User
Bullish	₹6,200	₹2,900
Neutral	₹3,800	₹1,400
Bearish	₹2,100	₹600

This demonstrates that, despite a higher short-term CPA, spend prioritisation is economically sound.

8.3.3 Attribution Robustness Test

Run attribution both with and without journey scoring.

Even if the system is flawed, it is causally significant if eliminating the scoring signal reduces long-term performance.

8.4 Economic Truth: Long-Term Validation (90–365 Days)

The only really important question is addressed by long-term validation: Did this solution improve enterprise value?

8.4.1 Incremental CLV Lift (Primary KPI)

$$CLV\ Lift = \frac{Avg\ CLV\_{Scored} - Avg\ CLV\_{Holdout}}{Avg\ CLV\_{Holdout}}$$

Holdout groups are required.

At scale, **even a 5–10% CLV** lift compounds enormously.

8.4.2 Payback Period Compression

Measure:

1. Time to break even on CAC
2. Time to reach contribution margin positivity

Bullish cohorts should reach payback **faster**, even if acquisition cost is higher.

8.4.3 Portfolio-Level Stability

Assess:

1. Revenue volatility
2. Churn variance
3. Discount dependency

CLV driven systems should **stabilize growth**, not just maximize peaks.

8.5 Optimization Levers (How to Improve Without Overfitting)

Optimization focuses on **structure**, not constant tuning.

8.5.1 Event Set Optimization (Quarterly)

Questions to ask:

1. Which events stopped differentiating cohorts?
2. Are new behaviors emerging?

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Action:

1. Retire low-signal events
2. Introduce new intent markers

8.5.2 Score Magnitude Calibration (Not Re-ranking)

Avoid frequent reweighting.

Instead:

1. Cap extreme scores
2. Normalize distributions
3. Adjust decay functions

This maintains **system stability**.

8.5.3 Creative-Score Feedback Loop

Identify:

1. Creatives over-indexed in bearish cohorts
2. Creatives consistently producing bullish trajectories

Shift budget accordingly.

Creative optimization becomes **strategic, not reactive**.

8.6 Governance Metrics

Metric	Why It Matters
Score volatility	Detects noise amplification
% users classified	Prevents overconfidence
Human override rate	Signals trust calibration
Model drift	Flags behavior change

A healthy system is **stable, explainable, and trusted**.

8.7 Failure Detection & Course Correction

Symptom	Diagnosis	Action
Bullish CPA rising	Healthy signal	Hold
No cohort separation	Weak events	Redesign
Platform overbidding	Feedback loop	Budget caps
Team ignores scores	Trust gap	Education

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9. WHY CREATIVE STRATEGY IS CENTRAL (NOT PERIPHERAL)

Most performance marketing systems treat creative as:

1. a **stimulus** to trigger a click
2. evaluated via **CTR, CVR, thumb-stop rate**

This is structurally flawed.

Creative is the **first economic contract** between the user and the brand.
It pre-selects customers by:

1. Expectations it sets
2. Identities it attracts
3. Trade-offs it signals (price vs value, speed vs quality)

Creative determines *who* converts—not just *whether* they convert.

Therefore, in a CLV driven system, Creative is **upstream of value**, not downstream of attribution.

9.2. Reframing Creative: From Conversion Lever to Selection Mechanism

Key Concept

Creative acts as a **filter** on the demand curve.

Creative Type	Who It Attracts	Long-Run Risk
Discount-led	Price-sensitive	High churn, low margin
Feature-led	Problem-aware	Medium CLV
Narrative-led	Identity-aligned	High retention
Proof-led	Risk-averse	Slower conversion, higher trust

A CLV system must **intentionally bias creative exposure** toward customers whose behaviors historically produce higher lifetime value.

9.3. Creative Taxonomy (Operational, Not Stylistic)

Creative is classified by **economic function**, not format.

9.3.1 Core Creative Archetypes

Archetype	Economic Role	Typical Signal
Incentive	Accelerates conversion	Short-term lift
Utility	Reduces friction	Medium intent
Proof	Builds trust	Slower funnel
Narrative	Aligns identity	High CLV
Community	Reinforces belonging	Retention

This taxonomy becomes **machine-readable metadata**, not just strategy language.

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9.4. Creative → Behavioral Signal → CLV Loop (Mechanism)

Core Loop

Creative Exposure

→ Behavioral Events

→ Journey Score

→ Cohort Quality

→ Media Reallocation

→ Creative Reprioritization

Creative does not get “optimized” directly.
It is optimized **via the quality of trajectories it initiates**.

9.5. Practical Implementation: Creative Strategy on the Ground

Example Context

D2C wellness subscription brand

9.5.1 Step 1: Tag Creative with Strategic Intent

Each creative is tagged **before launch**.

Creative ID	Archetype	Hypothesis
C01	Discount	Increases trial volume
C02	Narrative	Attracts long-term users
C03	Proof	Improves trust for high-AOV
C04	Utility	Reduces onboarding friction

This tagging is **mandatory** for learning.

9.5.2 Step 2: Route Creative to Controlled Audiences

Creative is not shown randomly.

Audience	Creative Bias
Cold / Broad	Narrative + Proof
High-intent retargeting	Utility
Low-score retargeting	Incentive
High-score nurture	Community

This prevents **value leakage**.

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9.5.3 Step 3: Measure Creative by Journey Quality (Not CTR)

Creative Evaluation Table

Creative	CTR	Avg Journey Score	Bullish %
Discount	2.8%	+14	9%
Narrative	1.1%	+46	37%
Utility	1.9%	+29	22%
Proof	1.3%	+34	26%

Traditional systems would kill Narrative.
CLV systems **scale it**.

9.6. Creative-Specific Optimization Rules

Creative priority changes by **journey stage**.

Journey Score	Creative Type
<20	Incentive
20–40	Utility
40–60	Proof
>60	Community / Brand

Creative becomes **sequenced**, not static.

9.7. Creative Failure Modes (Critical Nuances)

9.7.1 The "False Positive" Creative

High CTR + low journey scores
→ Attracts misaligned users

Fix: Cap exposure, not delete

9.7.2 The "Slow Burn" Creative

Low CTR + high CLV
→ Often narrative or brand

Fix: Protect with separate KPIs

9.7.3 Creative Overfitting

Optimizing narrative too narrowly
→ Audience shrinkage

Fix: Rotate narratives quarterly

10. THEORETICAL CONTRIBUTIONS

This research reconceptualizes paid media as a longitudinal, anticipatory value allocation system rather than a short-term performance tool, advancing theory in four ways. First, it prioritises future customer quality over immediate results by moving away from reactive attribution and towards predictive CLV driven decision-making. Second, it presents CLV as a governance system that, in the face of uncertainty and privacy restrictions, coordinates spend,

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attribution, and creative strategy. Third, by including CLV signals to direct organisational behaviour towards long-term value, it presents attribution as an incentive design challenge. Lastly, it reinterprets creative strategy as a cohort quality-shaping demand filter. When taken as a whole, these observations bring CLV driven paid media theory together in platform-mediated, privacy-constrained environments.

11. CONCLUSION

These days, digital advertising blends sophisticated automation with decision frameworks that are still based on quick, observable results. This article contends that the main obstacle to long-term profitability in modern commercial media ecosystems is this conceptual mismatch rather than a technical one.

The study rethinks paid media as a long-term investment in customer relationships rather than a transactional acquisition channel by implementing a predictive, Customer Lifetime Value-driven framework based on behavioural event scoring. Spend allocation, attribution, creative strategy, and dynamic conversion valuation are all integrated into a single governance system that is focused on long-term economic impact.

The method, which was created for settings with limited privacy, gives organisational sense-making, cohort-level learning, and probabilistic inference precedence over deterministic attribution. By doing this, it offers a theoretical and practical basis for coordinating paid media strategy with platform governance, legal requirements, and long-term growth goals. The study's conclusion is that success in digital advertising should be redefined, moving from maximising short-term efficiency to anticipating and fostering long-term value.

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