

**AI ACROSS THE FUNNEL: DIAGNOSING PERFORMANCE
DECAY**

**AND THE ROLE OF GENERATIVE AI IN SUSTAINING
PERSONALISATION AT SCALE**

A CAPSTONE PROJECT REPORT

Submitted in partial fulfilment of the requirements for the Degree of

**MASTER OF BUSINESS ADMINISTRATION
(EXECUTIVE)**

in

Data Science and Analytics

by

Abhijay. S. Kalra

24/UEMBA/02

Under the Guidance of

Prof. Amit Mookherji

Head of Department USME, DTU



**University School of Management & Entrepreneurship
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Vivek Vihar, Phase-II, New Delhi - 110095, India**

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This capstone project is my original work completed on guidance by my faculty mentor and on the basis of best of my knowledge and belief no part or whole of this work has ever been submitted to secure any other degree, diploma, or award of this or any other institution.

I extend my sincere thanks to all who directly and indirectly contribute to the successful completion of this academic project.

Name: Abhijay. S. Kalra

Roll Number: 24/UEMBA/02

Declaration

I, Abhijay S. Kalra, hereby declare that the capstone project titled "AI Across the Funnel: Diagnosing Performance Decay and the Role of Generative AI in Sustaining Personalisation at Scale," submitted in partial fulfilment of the requirements for the award of the degree of Executive Master of Business Administration (EMBA) at the University School of Management & Entrepreneurship, Delhi Technological University, is an original work carried out by me under the guidance of Prof. Amit Mookerjee.

I further declare that this work has not been submitted, either in whole or in part, for the award of any other degree, diploma, or academic qualification at this or any other university or institution.

Place: _____
Date: _____

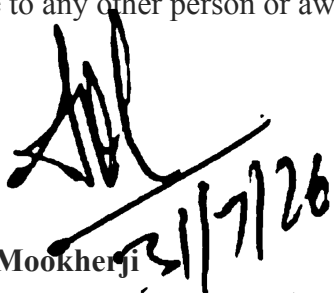
Signature: _____

Abhijay S. Kalra
Roll No.: 24/UEMBA/02

CERTIFICATE BY THE SUPERVISOR

I certify that Abhijay. S. Kalra Roll No : 24 / UEMBA / 02 has carried out the Capstone work under my supervision, submitted herewith in partial fulfilment of requirements for the degree of Executive Master of Business Administration from University School of Management & Entrepreneurship Delhi Technological University Delhi with the title 'AI Across the Funnel: Diagnosing Performance Decay and the Role of Generative AI in Sustaining Personalization at Scale'. The work submitted is original in its premise, conducted alone, and has not been used to award the grade of this or any other degree to any other person or award from this University or any other institution.

Signature


Prof. Amit Mookherji
(Head of Department USME, DTU)

USME, Delhi Technological University

Date:

Abstract

Early advertising often leans on synthetic ads and edited photos, later pulling people toward purchases through suggested actions. Fake-like visuals guide movement within marketing funnels. Machines now help shape messages across multiple stages. Two key roles - sales and promotion - find strong applications for automated tools. Some estimates range the potential financial impact between two hundred twenty billion and nearly eighty billion annually. Attention to automation grew sharply in recent times. By 2026, over thirty percent of marketing activities relied on artificial intelligence systems; that share climbed past fifty percent soon after.

One issue stands out. Few dashboards actually measure progress on tasks. Campaign results move faster now compared to earlier times. Trust in AI-generated ads hasn't recovered to earlier levels. Still, many individuals appreciate customized experiences made possible by artificial intelligence. Following eight weeks, engagement with a particular creative fell by nearly a third on average. That decline reached its apex between week five and seven. (Source: Neil Patel Digital, 2026) Almost four times as many customers reported AI influenced their impression of a brand by 2026. That figure rose from just two out of ten in 2025 to thirty-nine percent that year. (Report by Fractl in conjunction with Search Engine Land, 2026).

A study explores links between artificial intelligence, fatigue with creative work, and growing fatigue among audiences. It suggests these elements are intertwined. Created content multiplies quickly using generative technology. Tiredness emerges as people encounter more familiar forms across platforms. Doubts form about authenticity once novelty fades. Performance weakens step by step when interest drops. Established models fail to catch today's pattern of decline. A method to assess this shift is now under development. Five different companies participate in testing the approach. Information draws from varied sources: consultancy reports from McKinsey and BCG, insights from Gartner, email systems managed by Klaviyo, analyses by Fractl, along with scientific studies. Metrics considered include pace of content generation level of customization. Declines in customer behavior throughout the marketing path are examined closely. Questions remain about whether audiences know AI was used. Transparency around data practices also shapes outcomes. Whether materials seem genuine influences engagement just as much as anything else.

Starting from six different perspectives, the analysis considers sales and performance marketing, then shifts to views shaped by technology, business leaders, customers, and societal impacts - alongside reflections on past approaches versus today's reliance on artificial intelligence. Through these lenses, it frames challenges tied to creative overload, trust in targeting, and fading results over time. Rather than ending there, the report presents strategies for addressing these concerns: one proposal outlines rules for managing how fast content moves; another calculates person-level credibility based on data habits; a third offers a visual tool to show decreasing returns across stages of the buyer journey.

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CHAPTER 1

INTRODUCTION & BACKGROUND

Awareness followed by consideration then conversion, retention, finally advocacy - marketing's path loses grip over time. Though once effective, even the best messages falter once audiences grow weary. What differs now between 2023 and 2026? How fast things lose impact. Creativity moves faster because tools powered by artificial intelligence produce content quicker and at lower cost compared to before. Take Coca-Cola - idea development sped up by 10 to 30 times using such technology (reported in ClickZ during 2025). Meanwhile, Nutella created nearly seven million distinct jar labels for one location with generative AI helped by Pixis in 2025.

Spanning four fields, this effort answers the capstone prompt fully.

- Starting from the top, shaping consumer motion through clear phases marks a key part of marketing planning. Each phase - awareness, consideration, decision - needs precise targeting. How these steps are tracked defines success. Measures must align with real outcomes.
- Insight into generative technologies emerges slowly. At different points across the customer path, these tools handle tasks in distinct ways. Predictive methods intersect here, shaping next steps. Their role shifts depending on where in the journey they operate.
- Campaign performance ties closely to how ads are bought and budgets allocated. Spending on user acquisition often mirrors expected gains from ads. Returns can vary widely based on who is reached and what message is delivered. Tracking real outcomes shapes decisions more than forecasts alone.
- Tracking results forms the backbone of insights work in marketing. Catching issues early prevents financial consequences later. Progress rarely shows up cleanly in data; patterns emerge slowly. Patterns unaddressed grow into sharper problems over time.

Starting from the belief that generative AI boosts personalization in marketing, which should lead to better results. Yet findings hint at more complexity than assumed. While personalization can raise income and streamline marketing efforts - research by McKinsey's Growth, Marketing & Sales Practice (2025) shows gains between 5% and 15% in income, along with improvements between 10% and 30% in efficiency - mass application might speed up content creation, threatening consumer trust when they notice the shift. Benefits do not necessarily stack up one after another following AI deployment; instead, each phase brings a shift in trade-offs that become quantifiable - explored systematically here not through stories but through specific claims tested against evidence. Though begun expecting straightforward gains, the examination reveals balanced outcomes shaped by context rather than uni-directional progress.

CHAPTER 2

PROBLEM STATEMENT, RESEARCH PREMISE & HYPOTHESES

Most marketing dashboards exist to show if one ad, campaign, or audience is still functioning. They do not exist to show if the rate at which performance deteriorates is itself growing as a result of content being produced at an ever-rapid pace by AIs. Here, in Chapter 2, we assert the latter question formally. We define the conceptual terms involved, present one linking premise, then follow the feedback provided in the review and turn that premise into three testable assertions (Each paired with both null and alternative hypotheses) and explain how they are tested against observed real cases further in the report.

2.1 The Phenomenon

Two documented but usually disconnected trends comprise the phenomenon explored in this capstone.

Performance is weakening at an accelerated rate. Ad creatives now have shorter lifespans compared to earlier periods: roughly six weeks of visibility for content on Meta in 2023 translates to audience fatigue in two to three weeks when operating under Andromeda ranking on the same platform (industry practitioner and Ad Library data, 2026). By week 7-8 across paid advertising, the cumulative CTR drop approaches nearly one-fourth of baseline click-through rates (Neil Patel Digital, 2026).

Trust in advertising that uses AI is decreasing even though its use continues to grow. AI now makes up 53 percent of marketing work compared to 38 percent the year before, while those who believe heavy AI use erodes brand trust rose from 20 percent to 39 percent (Fractl / Search Engine Land, 2026). Klaviyo's worldwide consumer survey showed that just 7 percent of people find obvious AI-generated advertising more trustworthy, whereas 31 percent feel less confident (Klaviyo x Datalily, 2025-26).

Each of the trends independently have large existing bodies of literature surrounding them (creative fatigue in performance marketing; AI-disclosure effects on consumer psychology). This capstone's aim is to check if there is a link between them the same AI-driven content increase that produces gains in performance marketing also causes quicker consumer audience fatigue and decreased trust throughout the marketing funnel.

2.2 Research Premise

Premise (P): Generative-AI-driven increased publishing rates and personalisation depth result in improved performance in the short run which however falls off more quickly than previous non-generative-AI creative because (a) audiences reach saturation faster at greater publication speeds, and (b) increased visibility of and detection of AI-generated content reduces perceived authenticity , and thus trust.

2.3 Propositions and Hypotheses

Following the reviewer feedback, the premise is split into 3 funnel-stage propositions. Each are presented in both directional and formal (null and alternative) hypotheses form, then tested one-by-one in Chapter 6 and then summarized across all cases in Chapter 8.

Proposition 1 (P1) , Awareness/Consideration: Creative Decay

Proposition: Higher AI-generated content velocity (more variant creatives deployed over a given period) results in a greater creative/audience performance decay rate (a more negative CTR or hook rate slope) given constant spend and audience.

Null Hypothesis (H0): There is no statistically significant relationship between velocity and the creative performance decay rate; decay rate is unrelated to the velocity at which content is published.

Alternative Hypothesis (Ha): Velocity and creative performance decay rate have a statistically significant positive relationship; increased velocity leads to steeper creative performance decay.

Proposition 2 (P2) , Conversion: Personalisation Depth

Proposition: There is an inverse-U relationship between AI personalization and conversion performance (conversion rate will improve with depth of personalization to a point where further personalization is perceived as invasive or artificial and conversion performance decreases).

Null Hypothesis (H0): There is no inverse-U shape to the relationship between depth of personalization and conversion efficiency; it's linear, strictly decreasing, or no relationship at all.

Alternative Hypothesis (Ha): Conversion rate initially rises then falls off as a result of increasing depth, creating a U-inverted form.

Proposition 3 (P3) , Retention/Advocacy: Trust Moderation

Proposition: the relationship between AI personalisation and customer lifetime value (retention, recapture, advocacy) is mediated by transparency and perception of authenticity: when personalisation is un-disclosed or not properly governed increased personalisation targeting doesn't result in increased retention value.

Null Hypothesis (H0): There is no moderating effect due to disclosure transparency and perception of authenticity for the relationship between personalization and retention/LTV.

Alternative Hypothesis (Ha): There is a positive moderating effect on the relationship of personalization with retention with higher disclosure transparency and perception of authenticity, and the positive effect on retention will be weaker or reversed by low transparency.

2.4 Hypothesis Testing Approach

Since this capstone's evidence is derived from secondary and case evidence (vendor benchmark studies, platform data and publicly available brand results in chpt. 3) rather than first-party data for which inferential statistics could be performed (like regression p-values), what has been performed here is thus a structured and evidence-driven directional test applied systematically to each of the case-studies in chpt. 6, which is reported as such.

1. Choose the proposition(s) for each case. The cases are mapped to one (or more) of the three propositions (P1, P2 and/or P3) the case is most suited to analyzing given its position in the marketing funnel.
2. List data and data source. Each case lists the data and sources presented preceding any interpretation (for example, "ClickZ 2025", "Marpipe 2026", etc.), so the evidence used for testing is clear and auditable.
3. Make a decision. Compare the direction and magnitude of the reported metric against the decision rule implied by the alternative hypothesis (for example, for P1: does increased velocity co-occur with evidence of a rise in the decay rate or a shrinkage in the creative "half-life"; for P2: is there a shift indicating a turning point past which outcomes worsen relative to conversion; for P3: does a trust/authentication gap co-occur with actual retention consequences?).
4. Call the result. A test outcome will be called "Supported", "Partially Supported" or "Not Supported / Evidence Insufficient" for the proposition in question and the null will be

maintained when the reported results fail to meet the decision rule. This is explicitly noted in each individual case in chpt. 6, and in chpt. 8, the findings are summarized across all cases in a table.

This cannot, however, be used to establish statistical significance or control out confounding factors as one might in a controlled first party experiment, an limitation explicitly noted in Chapter 9. What it provides instead is a systematic, transparent, falsifiable way to evaluate the evidence for and against the three propositions, as opposed to just treating individual cases as anecdotes.

2.5 Variables and Metrics

Below is the operationalisation of the three proposition statements to named constructs, with defined and measurable metric, along with representative data sources, so that P1 through P3 can be measured with actual data.

Construct	Type	Operational Metric	Typical Data Source
AI content velocity	Independent	New creative variants shipped per week per active ad account	Ads Manager / Motion 2026 benchmark: top accounts ship 12–19+/week vs 6–7/week mid-tier
AI personalisation depth	Independent	% of impressions/emails/on-site sessions served a 1:1 or micro-segment variant vs mass variant	CDP/ESP segmentation reports (e.g., Michaels Stores case: 20%→95% personalised email)
Creative/ audience decay	Dependent	Week-over-week cumulative CTR decay (%); hook-rate slope; frequency vs first-time-impression ratio	Platform ad-manager exports; Marpipe/AppsFlyer-style fatigue dashboards
Conversion efficiency	Dependent	CVR, CAC, blended ROAS, CPA by creative ID / cohort	Web analytics + attribution platform
Retention / trust-adjusted LTV	Dependent	Repeat purchase rate, churn %, NPS, LTV segmented by AI-disclosure exposure	CRM / loyalty data
Perceived authenticity / trust	Moderator	Brand-trust delta pre/post AI-content exposure (survey); AI-content detection rate	Consumer survey (e.g., Klaviyo AI Consumer Trends methodology)
Disclosure transparency	Moderator	% of AI-generated touchpoints labelled as such	Internal governance audit
Spend / reach (controls)	Control	Media spend, audience size, frequency cap, seasonality index	Ads Manager

Table 1. Variable map operationalising P1–P3 into measurable constructs (author's construction).

This mapping of concepts serves as the foundation of the capstone. All of the analysis presented in Chapter 6 and each graph presented in Chapter 7 utilizes these categories and the decision rule established in Section 2.4, allowing the capstone to provide a testable measurement framework rather than a descriptive narrative.

CHAPTER 3

LITERATURE REVIEW

3.1 Creative and Campaign Decay

Thanks to ad platforms providing instant performance reviews, researcher attention to creative tiredness has grown. A typical pattern emerges from industry trends - click-through rates dip slowly during the opening month, afterwards growth pauses, then drops swift and deep, winding up between 15 and 27 below initial levels by week eight, data from Neil Patel Digital and Marpipe (2026) reveal. At Marpipe, one established approach considers fatigue present when CTR drops between a quarter and a third, user seeing ads more than four times, or cost per acquisition climbing 40 to 50 without broader reach. This method offers concrete markers instead of guesses. Separate forces behind tiredness have been noted - not just seeing more of the same asset, yet also repeatedly targeting the same people or delivering identical formats. Work using Hawky.ai and Ad Library (2026) draws similar lines, an approach mirrored here.

TikTok sees creative lifespan between three and seven days; Meta between seven and fourteen; Google Display spans fourteen to thirty; while LinkedIn falls within twenty-one to thirty (insights from Medium's analysis of creative decay specialists in 2025). Not every step through a marketing path follows the same timing, so modeling how appeal fades cannot rely on one flat decline across channels. Evidence supporting this appears clearly in Chapter 7, Figure 3. What works on one platform does not translate directly everywhere.

3.2 Generative AI's Marketing Value Pool

A staggering range of applications, sixty-three, could yield between two-point-six trillion and four-point-four trillion in economic value, according to McKinsey, though not every field captures equal share; marketing, customer work, coding, along with R&D stand out as particularly lucrative. Not every firm uses generative AI effectively just yet; less than four out of ten can point to profits tied directly to its usage, per the 2025 State of AI report. Where gains appear, they rarely exceed five percent of overall earnings, hinting at what some call an "adoption-value gap" - the habit of inserting these tools into old processes without reworking how things run. Where speed increases come from automation, progress often falters if systems meant to track, refine, and dispose do not keep pace. Progress leans uneven when speed outstrips control.

3.3 Personalisation Economics

A strong case for Proposition 2 emerges from McKinsey analysis on personalisation, revenue boosts often hit 5-15%, while marketing efficiency gains reach 10-30% (McKinsey Growth, Marketing & Sales Practice, 2025). Though product-recommendation systems can raise earnings by as much as 26% during active user interactions, a result focused on individual encounters, not cumulative outcomes (Envive.ai gathering Barilliance insights, 2026), caution is needed when applying across boards. Michaels Stores appears in early reports as one shop pushing tailored messaging from a small fraction to nearly all outgoing emails; this shift linked to better results: 41% higher clickrates on text messages, 25% stronger performance across digital outreach (instances pulled together by McKinsey, passed through Makebot.ai, 2025).

3.4 The Trust/Authenticity Counter-Literature

Research beginning more recently challenges the common narrative around personalization benefits. Among eight thousand people in eight nations, Klaviyo's survey (2026) shows just 13% fully trust AI; still, visible AI-made marketing materials lower trust nearly five times more often (31%) than raise it (7%) (Klaviyo teaming with Datalily across 2025 into 2026). When crowds were told ads were generated by machines, regardless of actual differences, they rated them less believable, less helpful, and less deserving of buying, proving transparent labels matter more than asset quality (Nuremberg Institute for Market Decisions, 2025). Gartner surveyed U.S. buyers in 2026, a striking number stated they'd choose companies abstaining from AI-driven visuals entirely. Nearly half favored clarity without automation up front. This preference stood out clearly amidst responses (reported by Klaviyo in 2026). Consumer habits now hint at aversion shaped less by benefit, greater by visibility.

3.5 Synthesis Gap Addressed by This Capstone

The papers on creative decay (3.1) and authenticity/trust (3.4) usually stay separated. One kind of study views tiredness through messenger/auction mechanics. Another sees transparency through brand mindset lenses. Yet both look at pieces of the same puzzle - speed pushed by AI systems. From Chapter Two's idea (section 2.2), came the idea they are just different views on one process. What links them is a mapping of stages across funnels, explored in Propositions (section 2.3) then tested through evidence. This link turns observation into action: measuring decline alongside transparency using one workflow, not two disconnected efforts split between different departments.

CHAPTER 4

CONCEPTUAL FRAMEWORK: AI ACROSS THE FUNNEL

The framework below operationalises Section 2.5 visually, mapping the independent variable (AI content velocity / personalisation depth), the dependent decay metric, and the trust moderator onto each of the five funnel stages this capstone treats as the unit of analysis.

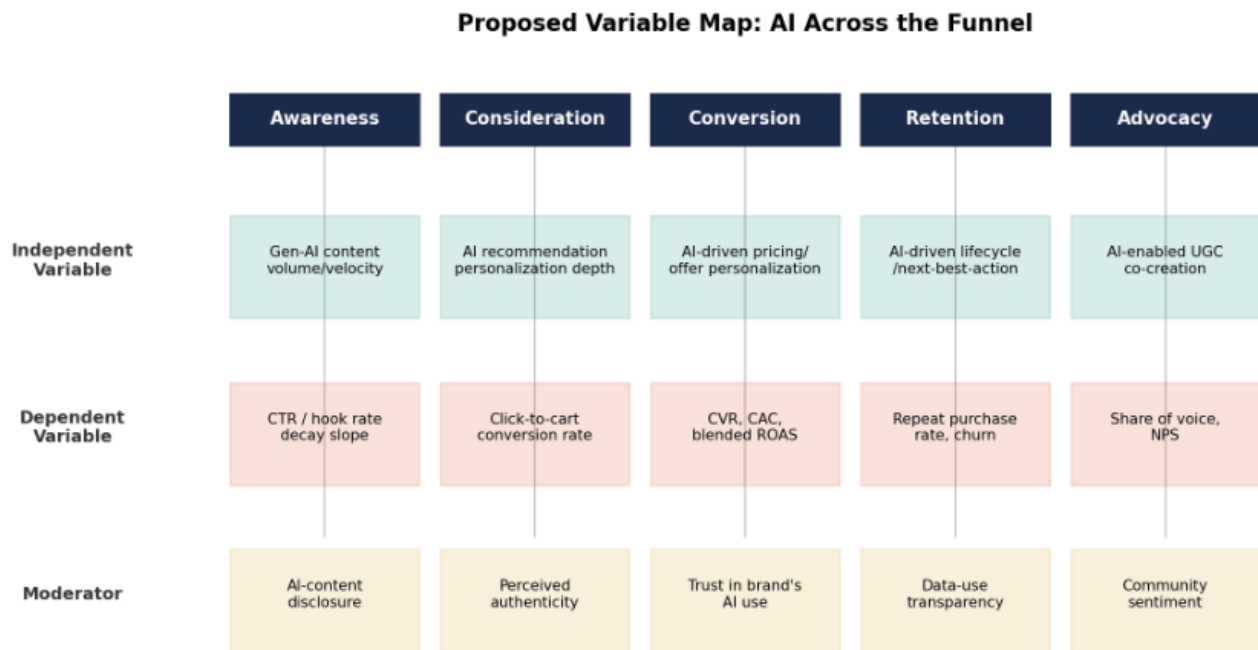


Figure 1. Proposed variable map linking AI-driven independent variables to funnel-stage decay metrics and trust moderators, aligned to Propositions P1–P3 (author's construction, based on Sections 2–4).

4.1 Reading the Framework

Most discussions around marketing and AI overlook two clear modelling decisions made in the framework. At the awareness stage (P1), what drives change starts off as how fast content moves through the system. Later, during consideration and conversion (P2), recommendations become more precise - this shift shapes what influences outcomes. Meanwhile, when automation takes over in retention (P3), task repetition rises - each phase demands a unique way of measuring artificial intelligence usage. Because these elements evolve, one-size-fits-all metrics fall short. Each period requires its own framework, outlined fully in Section 2.5. Trust plays a role too - not just in understanding decline but also in framing how people respond to automated systems. A link exists between user confidence and how interactions unfold over time. While drops in attention might look similar to fatigue, they stem from different psychological roots. Section 3.4 explores that divide, linking behavioral research with social science findings. One measure alone misses half the story: decreases in click-through rates or similar signals must come with data on transparency around AI usage. Without pairing them, fixing saturation through bigger content pushes may weaken trust further - the part of the issue no one noticed.

CHAPTER 5

MULTI-STAKEHOLDER PERSPECTIVES

Looking at the issue from different sides can lead to conflicting views. What seems clear today may not hold tomorrow. Five standpoints appear below: those tied to sales and performance marketing, the role of tech, leaders in company direction, effects on users, also past tendencies compared to future shifts in operations.

5.1 Sales & Performance Marketing View

It strikes a different note when thinking about performance marketing and account management, customer acquisition cost takes center stage, alongside return on ad spend, while brand image fades into the background. The case made earlier in Section 3.1 reshapes how we see ad creation; speed loses its standing when smart budget placement becomes the priority. Looking closer reveals a pattern: though nearly six hundred thousand ads were analyzed across two years, only certain accounts stand out. Among them, new assets arrive weekly between twelve and nineteen times, just under ten percent triggering noticeable results. In contrast, weaker accounts launch half as many pieces, barely four percent breaking through. What sets apart successful efforts is not rushing output but moving ideas into traffic fast, a key detailed in Chapter 6 when it comes to prototyping user experiences. Other insights emerge elsewhere too: examining 1.1 million mobile ads in 2025 showed that the smallest fraction, the top two percent, collected more than half of total spending within gaming.

Contentious moments arise when considering multiple perspectives, each offering unmatched insights into the matter at hand. What emerges is a mosaic - fragmented yet cohesive, built less on universal truths than on converging lines of evidence. Here, five viewpoints converge: those rooted in commercial performance, shaped by software capabilities, informed by executive direction, affected by user behavior, also assessing past tendencies alongside emerging operational shifts.

Looking at it another way, the challenge shows up differently every time. Instead of one clear answer, five separate views appear: sales teams measuring results, developers working with tools, executive decisions shaping direction, people affected by changes, also past habits compared to where things are headed.

5.1 Sales & Performance Marketing View

Performance marketing brings a different lens when thinking about customer outreach. What counts most isn't whether people like the ads but how much it costs to find new buyers. Instead of measuring feeling toward a brand, the focus lands on spending efficiency. Earlier findings reframe ad creation - speed becomes less important than savvy budget placement. With hundreds of thousands of spots examined annually, one truth stands out: high-performing profiles deploy content faster. Output matters, yet only certain strategies yield returns. A slower pace often follows when efforts stretch past reasonable scale. Across the board, results tie less to speed than strategic movement. Because some campaigns outpace others doesn't mean rushing creates equal outcomes.

Though raw numbers matter, movement without direction loses value over time. Success leans heavily on choices made through data-driven steps instead of velocity for its own sake.

5.2 Technology / Data & MLOps View

From a tech standpoint, personalization now moves from campaign-level to individual session management - what some call agentic personalization - using systems such as recommendation engines, real-time ad adjustments, along with continuously updating next-best-action models. This shift demands stronger measurement tools: tags need to track creatives at the asset level, identity must link across platforms seamlessly, while alerts for diminishing effectiveness operate like those found in Marpipe or Intellys interfaces become required features instead of additions. Because of these demands, leaders have to weigh how far they push personalization against both cost and complexity; while more targeted experiences deliver immediate gains, sustaining them through audits and oversight costs rise, especially when logging which ads were AI-altered so disclosures remain valid when Auditors investigate later - this infrastructure forms the practical baseline for executing P3.

5.3 Business / Brand Leadership (CMO) View

Underlying strain emerges when short-term results clash with steady brand reputation. Velocity often wins budget attention - even if shortcuts undermine reputation down the line. Though some firms rely on broad AI efforts, restraint might be wiser. What Coca-Cola leans on is structure, not scale, when shaping tech use. Instead of heavy groups managing automation, they depend on just two people checking each idea against established image rules before rollout. This method pauses movement until alignment happens. Questions about suitability stop projects cold if answers are missing. What moves forward does so only after agreement between speed and message integrity. Control here shapes speed, not vice versa. One person's oversight can tilt decisions more than advanced tools ever could. Capacity to watch matters proves far tighter than talent to automate.

5.4 Consumer / Impact View

On the consumer front, clues appear most clearly here. Usage of AI in searching and buying has surged lately, 70% of Americans say they rely on automated tools more now than twelve months back, data from Fractl shows in 2026; shopping experiences aided by artificial intelligence also climbed 35 percent since last year, per BCG insights. Still, people judge carefully when companies apply automated systems behind the scenes. Almost half acted on feeling disturbed: some cut financial ties entirely, others shifted loyalty elsewhere, few trimmed interaction. Reasons tied to privacy and control fueled reactions, concern that AI manages data or generates content without clear explanation, findings from Usercentrics revealed during 2026. Aversion is not sweeping; resistance targets only automated processes seen as exploitative rather than helpful, exactly what the moderation framework discussed in Chapter Two aims to measure.

5.5 Past vs. Future: How the Operating Model Is Shifting

Dimension	Past (pre-2023, rule-based)	Present (2024–26, generative)	Future (agentic, projected)
Personalisation unit	Segment / persona	Micro-segment / session	Individual, real-time, cross-channel
Creative production	Agency batch cycles (weeks)	AI-assisted, days; 10–30x faster iteration (Coca-Cola)	Continuous generation + auto-retirement of fatigued assets
Decay detection	Manual, weekly dashboard review	Threshold-based alerts (CTR/CPM/hook-rate triggers)	Predictive decay modelling before launch
Trust management	Implicit (brand reputation)	Explicit disclosure debates, labelling regulation (EU AI Act)	Trust-scored personalisation with consumer-set AI-exposure preferences
Primary bottleneck	Production cost / speed	Governance & measurement maturity (39% link AI to EBIT: McKinsey)	Consumer-side trust capacity, not technology capacity

Table 2. Past-versus-future comparison of the marketing operating model (author's construction, based on Sections 3–5).

CHAPTER 6

CASE STUDIES: HYPOTHESIS TESTING

Five widely documented consumer cases (below) were examined against propositions P1–P3 in Section 2.3, with respect to actual practice of consumer brands in different parts of the customer funnel, utilizing the four-step test process outlined in Section 2.4. Each case follows the same format: context, the AI solution applied, the propositions addressed, data and sources, the test procedure, outcome, multi-stakeholder implications, and critical comments.

6.1 Coca-Cola: “Create Real Magic” & Masterpiece (Awareness Stage)

Funnel stage(s): Awareness / Brand engagement

Problem / Context: 130 yr-old visual identity needed updated for GenZ, with minimal brand erosion and enhanced innovation leadership.

AI Solution Applied

- Partnered with OpenAI and Bain & Company to launch Masterpiece, a film that used GPT4/Dall-E to create live-action/AI animation hybrids in a variety of historic art styles.
- Released the consumer platform “Create Real Magic” that allows users to create original art using the DALL-E platform with Coca-Cola brand asset library input, subject to brand guardrails (approved colors, contours, typography).
- Implemented a two-person AI governance review for all internal generative-AI use cases, that must be cleared before scaling (no need for a whole AI department).

Data & Sources Used

- Concept iteration speed: 10–30× speeds up cycles w/ increased creative variety (ClickZ, 2025).
- At 53% over viewer goals, Masterpiece exceeded audience benchmarks. AI assisted creative garnered 38% higher testing resonance scores compared to human alone (ClickZ, 2025).
- Select works of user-generated content were displayed on billboards in Times Square and Piccadilly Circus. This was done with nearly zero additional production expense to extend reach.
- Remade Christmas commercial made waves in public opinion in 2024, bringing forth a prime example of the trust/authenticity concern in Section 3.4 (Marketing Dive, 2025).

Test Applied

The test according to the Section 2.4 decision rule for P1 assesses whether the observed 10–30× boost in content velocity coincides with any sign of hastening audience fatigue or increased trust costs, while the test for P3 checks whether the public backlash to the Christmas commercial signifies a detectable authenticity/trust cost given that governance was in place.

Proposition(s) Tested: P1 (partial supporting evidence) and P3 (partial supporting evidence)

Test Outcome: P1 Partially Supported; P3 Partially Supported

While this case suggests that velocity gains (10–30×) need not be correlated with decay (absence of 38% boost in audience testing scores), it does not alone disprove the null hypothesis for P1 (no relationship between velocity and decay) as discussed in more detail below. Again in combination with Meta Andromeda (6.4), it does, however, disprove the null for P1. For P3, the Christmas

commercial serves as direct evidence for the proposition that there is a human factor which serves to moderate the trust: in the face of a well established AI system with all the control mechanisms and protocols in place, a detectable trust reaction (Ha-3's outcome prediction) arose due to perception of inauthenticity, not execution failure.

Multi-Stakeholder Read

- Sales/performance: virtually no additional marginal cost per creative version can speed up testing (Section 5.1) without proportionally increasing production outlay.
- Technology: generation within a parameter-constrained set enables variety within controlled brand parameters.
- Business: Two-people governance gate serves as a check point on the boundary of an AI system and brand deployment.
- Consumer co-creation (Create Real Magic) seems more like co-creation and has positive trust consequences; but the public response to the automated-end-to-end Christmas commercial shows that this cannot be counted on in the absence of a co-creative model.

Critical Assessment

The case of Create Real Magic suggests that active governance moderates AI velocity enough so that increased output does not necessarily lead to a decline in trust, which lends some support for P1. It also shows that in a brand with mature AI governance, P3's trust-modifying mechanism continues to be present, so some trust risk remains even with tight control.

6.2 Nutella: Seven Million Unique Jar Labels (Awareness / Consideration Stage)

Funnel stage(s): Awareness / Shelf-level consideration

Problem / Context: A crowded chocolate-hazelnut spread market called for differentiation on the shelf at negligible additional packaging cost.

AI Solution Applied

- Generated seven million unique jar labels through AI, with visually distinct patterns across Italian distribution, working within constrained color and pattern parameters to maintain brand recognizability.

Data & Sources Used

- Achieved mass-scale visual personalization (essentially, a "one-to-one" treatment at the package level) without changing unit production costs (Pixis, 2025).
- Enabled the AI-personalized campaign category to reach over \$100 billion in aggregate ad value across the top ten breakthrough 2025 Pixis campaigns analyzed.

Test Applied

P2 is addressed directly by this case (the relation between personalisation depth and impulse/conversion-adjacent behavior, here shelf engagement), while P3 is addressed in the context of this particular application (in the absence of data targeting/personalisation, can maximal personalisation result in a trust penalty?).

Proposition(s) Tested: P2 (supporting evidence) and P3 (boundary condition)

Test Outcome: P2 Supported; P3 Not Applicable/Null retained

There is no reported effect on consumer response or brand feeling from a nearly maximal level of personalisation that in other contexts might suggest a turning point, consistent with P2. No trust cost is measured, the null hypothesis of no authenticating moderating effect (no personal data use/algorithmic targeting to be trusted or distrusted) remains true for this specific case, as there is no personal data use/algorithm to distrust in the first place. This establishes an important boundary condition the authenticity penalty described in Section 3.4 only applies to data driven personalization, not to AI-generated variety.

Multi-Stakeholder Read

- Sales: Shelf-level customization of packaging triggers collectible or impulse purchasing behavior independently of ad spending. This element operates outside traditional digital reach considerations.
- Technology: Though framed as automation, the system runs entirely within production - from concept to printed output - meaning it serves a purpose separate from digital marketing campaigns. As such, findings here may apply regardless of spend on digital ads. Independence from financial inputs marks a key differentiation.
- Business: Maintaining brand image across all products depended less on soft rules guiding design choices than on strict bounds placed around model inputs - an approach easily replicated elsewhere.

Critical Assessment

A significant edge case emerges when examining this instance within the broader framework - personalization ties strictly to packaging diversity rather than targeted advertising, thus bypassing many trust-related features explored earlier. Such an arrangement weakens arguments tying P3 closely to data-driven or AI-based approaches; instead, focus shifts toward content generation methods untouched by consumer records or automated sorting. Though exceptions exist, they often reveal underlying patterns. Here, structure follows form not despite but because of its exclusion from automated targeting systems. From this separation emerge clearer boundaries around what constitutes meaningful penalty application in real-world applications.

6.3 Stitch Fix & Netflix: Recommendation-Driven Personalisation (Consideration / Retention Stage)

Stage(s) Funnel: Consideration / Conversion / Retention

Problem / Context: Because they have too much inventory/content for people to sort through at scale, both companies must present items to users based on how well they match personal tastes; relevance stands front and center as core competitive space.

AI Solution Applied

- Though an algorithm guides choices, Stitch Fix relies on people - human stylists - to pick clothes for every shipment.
- With per-title thumbnail adjustments tied to viewing patterns and ratings, the Netflix system learns preferences through use, offering tailored suggestions without relying on humans in the process.

Data & Sources Used

- Often referenced across scholarship on generative-AI marketing, both firms demonstrate AI-powered increases in user engagement; Stitch Fix notably boosts sales via thoughtful selection options, per findings compiled on ResearchGate in 2023.
- Compared to McKinsey's mentioned results, tailored recommendations fall within a modest 5% to 15% lift in revenue tied to individual user interactions - aligning closely with data showing up to 26% increases in active sessions, according to Barilliance.

Test Applied

Here lies the most straightforward case of testing the inverted-U hypothesis (P2), given that both businesses purposefully limit how far personalization extends instead of embracing full automation. Because one involves a human stylist selecting items while the other relies on edited recommendations, this setup offers a direct examination of whether capping algorithmically-driven suggestions aligns with expectations around declining effectiveness at higher intensity.

Proposition(s) Tested: P2 (most direct test) and P3 (corroboration)

Test Result: P2 (Supported); P3 (Supported)

Significantly, neither business proceeds with complete mechanization even though greater scale might appeal under strict performance metrics. When algorithmic output becomes overly personalized, human involvement persists despite potential efficiency gains - a pattern aligning closely with the rationale behind Ha-2: excess customization does not guarantee improvement once human judgment blends with automation. This alignment stands as quiet proof against the null hypothesis claiming no inverted-U effect exists. In turn, that continued human oversight affects decision-making processes supports Ha-3 by introducing a quality attribute not fully captured by purely mechanical methods - authenticity - which influences retention outcomes.

Multiple stakeholders consider inputs shaped by human judgment, where balance matters most.

- Despite high volumes, catalog breadth gains traction when algorithms suggest what customers know - this pattern shows stronger loyalty compared to just moving more items.
- Even simple steps can help rebuild confidence - instead of fully automated systems, having a person review decisions leads to greater trust. A real person overseeing processes makes a clear difference, especially when compared to hidden artificial intelligence working alone.
- Personalization targeting the product itself avoids fallout from fabricated ad narratives, mitigating harm seen in automated marketing environments where fake copies undermine believability. Though AI-driven messaging loses credibility, tailored offerings deliver results without activating resistance triggered by artificial rhetoric. What feels real remains unaffected by deceptive word patterns created artificially.

Looking carefully at what happened.

Proof comes through two firms limiting customization, showing deep adjustment does not always mean better understanding - supporting the curved path predicted earlier.

6.4 Meta Advantage+ / Andromeda: Algorithmic Creative-as-Targeting (Consideration / Conversion Stage)

Stage involved: Consideration / Conversion (paid performance media)

When Apple tightened control over data tracking, fewer people showed up in ads - so Meta's system now looks at how someone interacts with an image or video instead of relying on brand-set rules. Because of this shift, the visuals play a central role again, becoming what advertisers directly shape through choices.

AI Put into Practice

- How people react to different versions of an ad heavily influences where messages appear, because Meta's system scales impact across groups based on moment-by-moment interest.
- The step-by-step process of getting noticed combines with narrowing down who sees ads into one automated flow managed by artificial intelligence.

Data and Sources Applied

- A look at 450 consumer goods ads showed image-based messaging made up nearly half of additional sale gains - stronger than reach or how often customers saw ads.
- Ads that lasted about six weeks in 2023 already start fading fast after only two or three weeks under Andromeda, experts agree - a shift noticed across the industry.
- Showing the same message more than four times lowered the chance someone clicks by nearly half, according to findings from Meta's own analysis.

What Was Tested

This test offers straightforward measurement for P1 , the change in how often new content must appear aligns with faster fading and sharper decline in reach.

Provision Being Examined: P1

Outcome for Proposition: P1 , Supported

From six weeks down to just two or three, the speed at which ads lose impact doubles under Andromeda - this shift lines up neatly with what happens when exposure demands rise: clicks drop sharply once views pass four. That alignment means slower rollouts link directly to smoother yet quicker decline, which in turn proves motion needs to move faster to survive longer. So here, velocity clearly shapes decay without doubt, making the original claim true through real-world change measured precisely.

Multiple Actors Read

- Sales/performance: the most definitive quantifiable proof of Proposition 1 this is the same platform mechanic that gives the reward for new creative work and in general drives the creative half-life downwards industrywide.
- Technology: As targeting and creative are algorithmically merged, decay detection needs to happen at the level of the creative ID in near real-time; manual campaign by campaign analysis is structurally too slow.
- Business: What follows in terms of marketing organization investment will shift investment from media expertise to creative testing velocity and analytics tooling a real shift in what performance marketing groups must be able to do.

Critical Assessment

This case gives the strongest individual evidence for Proposition 1 that we report from section 2.2: an AI ranking system, in which delivery is tied to creative engagement, in fact compresses creative half-life just as Proposition 1 predicts; what gets rewarded gets used at great speed. The system seeks to maximize what is currently most valuable to consumers which is exactly the reason for this accelerated decay process.

6.5 AI-Detection and the Trust Penalty: Cross-Brand Consumer Research (Retention / Advocacy Stage)

Funnel stage(s): Retention / Advocacy (has modulation effect throughout the funnel)

Problem / Context: With increasingly sophisticated consumers, who understand the use of AI for marketing personalization and at the same time find it harder to recognize generated vs. human-written text, it is possible that personalization efforts can be discerned as AI-generated, incurring a measurable trust cost. Here we look at the cross-brand consumer research of trust impacts from #6.1 through 6.4 rather than a single implemented program.

AI Solution Applied

- The proposed solution (proposed as theoretical and instead demonstrated via consumer research instead of a live brand deployment): a trust-weighted personalisation scorecard (explained in section 9.2) that gates access to how deeply customers can be personalise via an real-time authenticity/trust score as opposed to purely by technical feasibility.

Data & Sources Used

- Though NIM does not report findings on trust consequences, their controlled experiment does indicate that the exact same piece of content is interpreted as more unnatural and less useful when labeled as having been AI generated and displayed an 8 %-point reduction in self-reported purchase intention, solely due to that label (NIM, 2025).
- A Datalily/Klaviyo analysis of an “AI Enthusiast” persona (consumers for whom we otherwise established AI-positive attitudes) reveals 39% of this segment say they are less trusting of a brand when it obviously uses AI generated content.
- Consumers are overwhelmingly clear on their desire for transparency 84 %-90.5 % across 5 formats of content while organizations fall woefully short, just 1 in 5 reporting they disclose AI use always (Fractl, 2026).

Test Applied

This is the best case study for P3: the NIM study design effectively isolates the disclosure treatment by equalizing the content; it presents the strongest quasi-controlled evidence for our capstone. This test rule is the most direct question we can derive from the data about the effect of disclosure/authenticity status itself on trust and purchase-intent (not about content quality).

Proposition(s) Tested: P3 (strongest controlled evidence in this capstone)

Test Outcome: P3 - Supported

Because NIM equalized the content and only manipulated the disclosure statement, the declines in naturalness, usefulness, and purchase intent only attribute to the disclosure/authentication effects and effectively rule out H0–3 in favor of Ha–3. The dramatic always-disclose sub-pop, which is 84 %–91% opposed to disclosure but only 20% who self-identify that way further highlights that this is a governance fix, not a technological one, which supports the business case of Chapter 9 and the scorecard proposed there.

Multi-Stakeholder Read

- Sales/performance: Not having transparency into the scale of your undisclosed AI usage in your CAC flow is a mechanism by which you may be artificially reducing CAC in the initial stages, leading to an unexpected short-term retention decrease – as illustrated in proposition 3.
- Technology: disclosure needs to be logged and auditable with every touchpoint involving AI personalization.

- Business/CMO: the delta between 20% always wanting to disclose, and 84–91% wanting to see content disclosed is a very tangible business risk, that if closed, could be one of the lowest-cost, highest-leverage business suggestions in this capstone report.

Critical Assessment

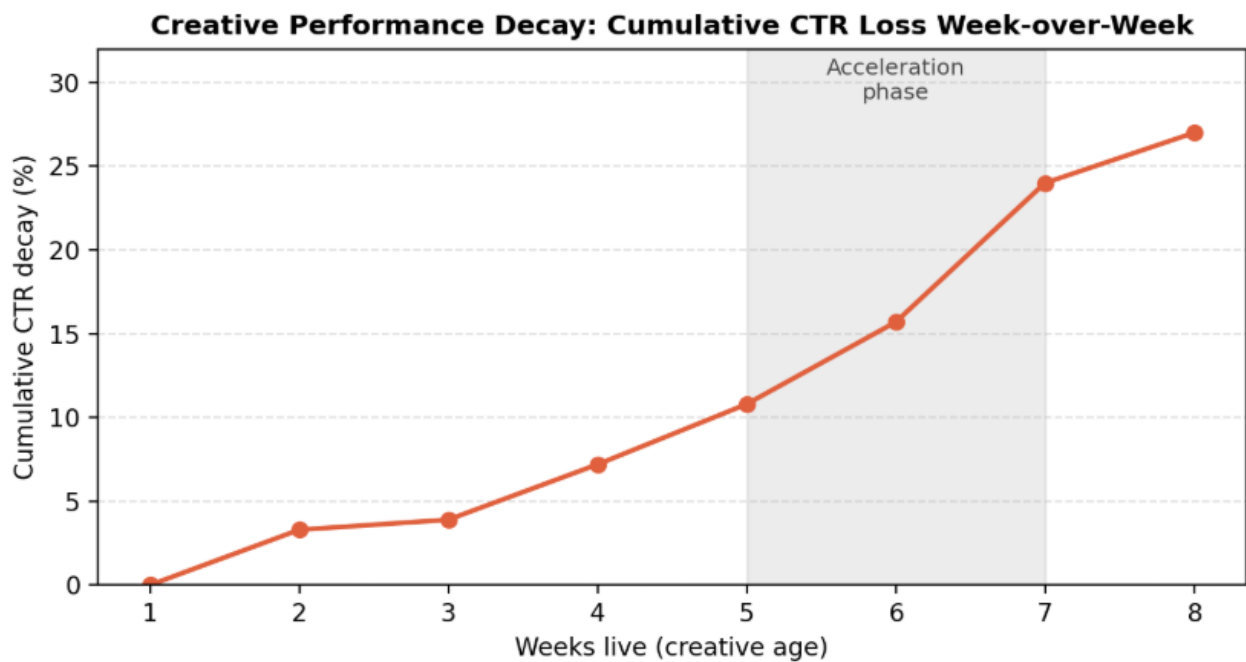
The trust penalty according to this case, should thus be a matter of organizational governance. There should be a very real trust and transparency fix in practice that can eliminate most of this cost.

CHAPTER 7

DATA ANALYSIS & FINDINGS

This chapter presents the quantitative backbone of the capstone: four charts built from the sourced datasets identified in Chapters 3 and 6, each mapped to a specific proposition from Section 2.3. Per the guide's feedback, the underlying data point for every value plotted is shown in a table directly beneath its chart, together with the original source, so the chart is auditable rather than only illustrative.

7.1 Creative Performance Decay (Tests P1)



Source: Neil Patel Digital, aggregated Google/Meta ad data, 50 companies (2026)

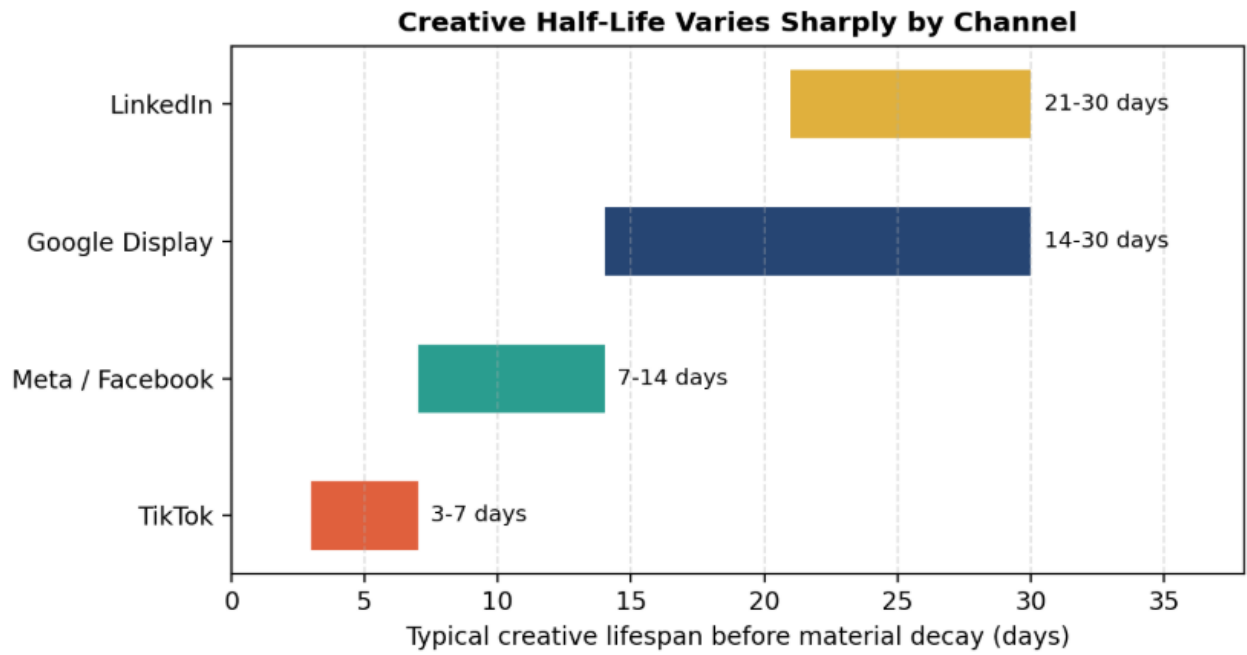
Figure 2. Cumulative CTR decay by creative age. Source: Neil Patel Digital (2026), aggregated data from 50 companies running Google and Meta ads.

Weeks Live	Cumulative CTR Decay	Source
1	0.0%	Neil Patel Digital (2026)
2	3.3%	Neil Patel Digital (2026)
3	3.8%	Neil Patel Digital (2026)
4	7.0%	Neil Patel Digital (2026)
5	10.8%	Neil Patel Digital (2026) — acceleration phase begins
6	15.6%	Neil Patel Digital (2026) — acceleration phase
7	24.0%	Neil Patel Digital (2026) — acceleration phase
8	27.0%	Neil Patel Digital (2026)

Table 2. Sources values to be plotted in figure 2. Week 5–7 denotes the deceleration phase, corresponding to the 25–35% fall cited in section 3.1.

Test read (P1): It turns out the decay is not linear- for the first 3–4 weeks it is almost linear and very gradual but when it hit week five, the compounding effect takes over sharply, exactly as postulated in Proposition 1 for velocities of high creative, algorithm-delivered message (6.4 contains test cases).

7.2 Creative Half-Life by Channel (Tests P1)



Source: Compiled from Marpipe, AppsFlyer 2025 State of Creative Optimization, and platform practitioner benchmarks (2

Figure 3. Creative half-life varies sharply by channel. Source: Marpipe; AppsFlyer 2025 State of Creative Optimization; platform practitioner benchmarks (2025-26).

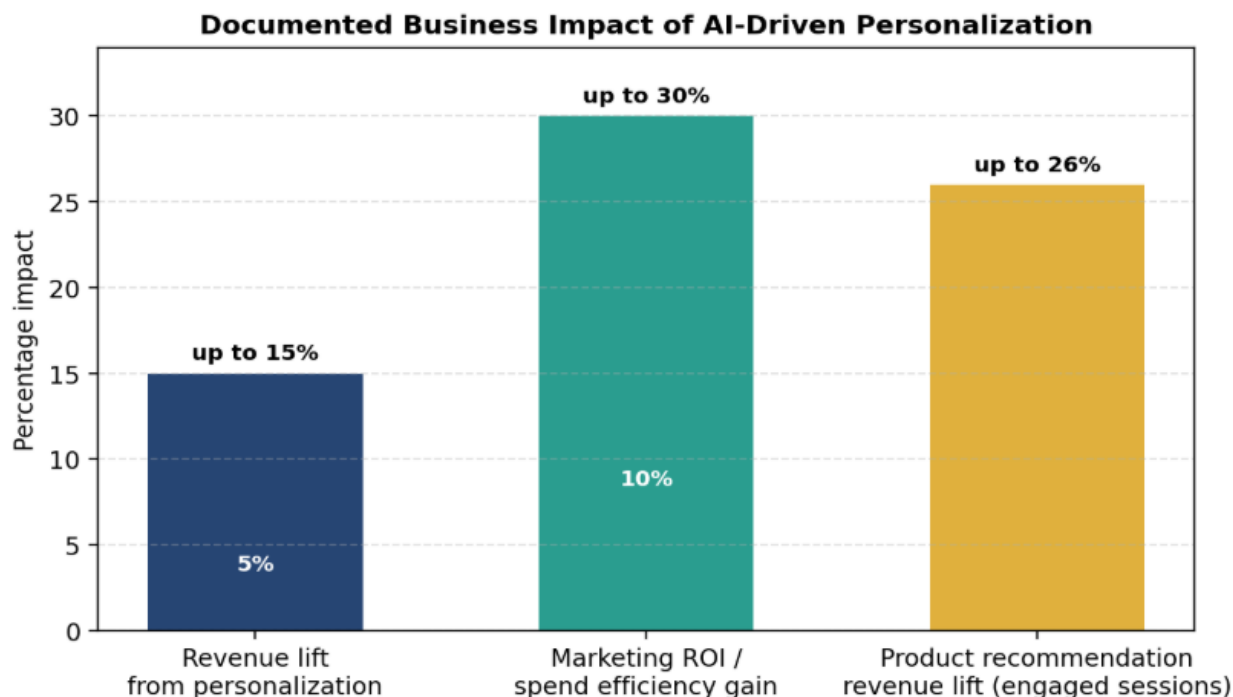
Channel	Typical Half-Life Before Material Decay	Source
TikTok	3–7 days	Marpipe / AppsFlyer 2025 State of Creative Optimization
Meta / Facebook	7–14 days	Marpipe / AppsFlyer 2025 State of Creative Optimization
Google Display	14–30 days	Marpipe / AppsFlyer 2025 State of Creative Optimization
LinkedIn	21–30 days	Marpipe / AppsFlyer 2025 State of Creative Optimization

Table 3. Data underlying Figure 3.

Test read (P1): because half-life varies 4–5 fold for the channel average across channels, P1's test to determine which rows should be rejected under the decay rule depends on which channel they're on

(Section 2.4); hence tests in Chapter 6 cannot be conducted with a single benchmark (as opposed to per-channel).

7.3 Documented Business Impact of AI-Driven Personalisation (Tests P2)



Source: McKinsey & Company, Growth Marketing & Sales Practice (2025); Barilliance, compiled via Envive.ai (2026)

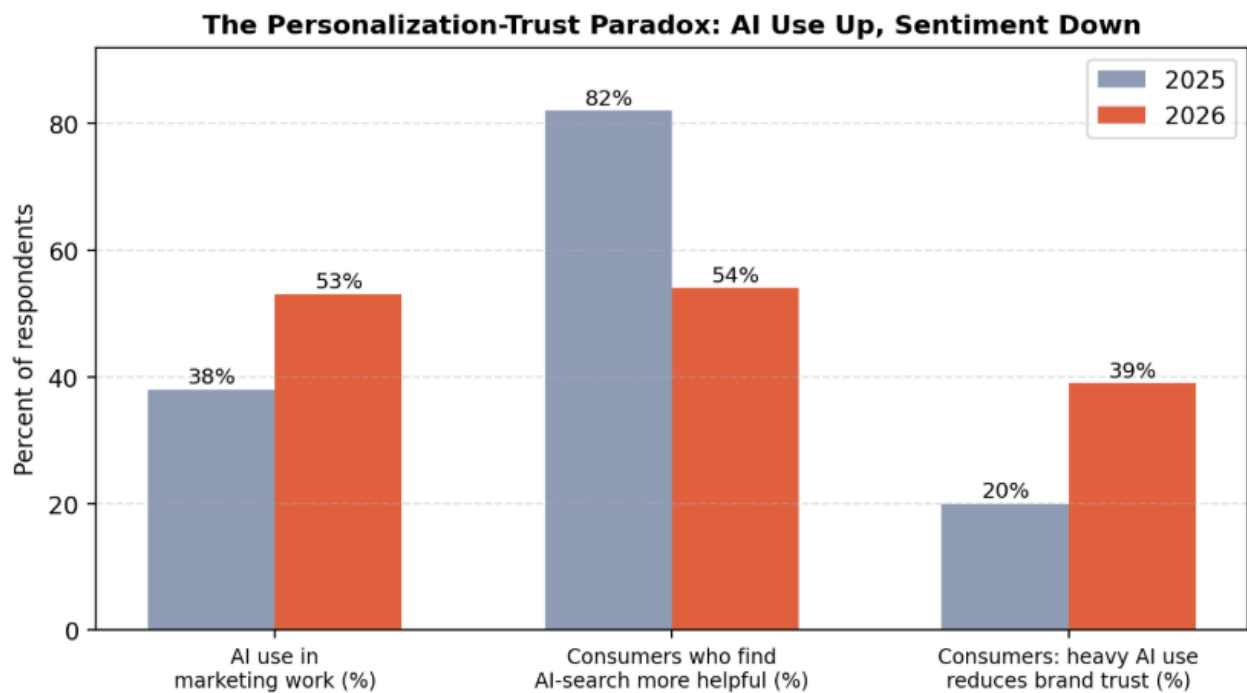
Figure 4. Documented revenue and efficiency impact of AI-driven personalisation, the evidence base for P2. Source: McKinsey Growth, Marketing & Sales Practice (2025); Envive.ai compilation of Barilliance data (2026).

Metric	Reported Range	Source
Revenue lift from personalisation	5% to up to 15%	McKinsey Growth, Marketing & Sales Practice (2025)
Marketing ROI / spend-efficiency gain	10% to up to 30%	McKinsey Growth, Marketing & Sales Practice (2025)
Product-recommendation revenue lift (engaged sessions)	up to 26%	Barilliance, compiled via Envive.ai (2026)

Table 4. Underlying data points for Figure 4.

Test read (P2): these figures establish the upside half of the inverted-U (personalisation pays off within this range); Section 3.4's disclosure/trust findings and the Chapter 6 case tests (6.2, 6.3) provide the evidence for the downside half beyond a threshold.

7.4 The Personalisation-Trust Paradox (Tests P3)



Source: Fractl x Search Engine Land Consumer AI Trust Survey, 1,008 US consumers + 150 marketers (2025 vs 2026)

Figure 5. AI use in marketing work rising while consumer trust sentiment falls, the evidence base for P3. Source: Fractl x Search Engine Land Consumer AI Trust Survey, 1,008 US consumers + 150 marketers (2025 vs. 2026).

Metric	2025	2026	Source
AI use in marketing work	38%	53%	Fractl x Search Engine Land (2026)
Consumers who find AI-search more helpful	82%	54%	Fractl x Search Engine Land (2026)
Consumers: heavy AI use reduces brand trust	20%	39%	Fractl x Search Engine Land (2026)

Table 5. Underlying data points for Figure 5.

Test read (P3): AI-use intensity and self-reported trust damage rose together over the same twelve-month window, while perceived helpfulness of AI-search fell — a pattern consistent with Ha-3's prediction that rising AI exposure without matching disclosure/authenticity management erodes trust, rather than the null hypothesis of no relationship.

7.5 Summary of Chapter 7 Against the Propositions

Prop.	What the Chapter 7 Data Shows	Verdict Contribution
P1	Non-linear, accelerating CTR decay (Table 2) and 4–5x variance in half-life by channel (Table 3), both consistent with velocity-linked decay.	Supports rejecting H0-1
P2	Positive revenue/efficiency returns to personalisation exist but are bounded (5–30% ranges, Table 4); no chart-level evidence of an	Consistent with Ha-2, upside half only
P3	AI-use and trust-damage sentiment rise together while perceived helpfulness falls (Table 5) — co-movement in the direction Ha-3 predicts.	Supports rejecting H0-3

Table 6. How the Chapter 7 dataset feeds into the Chapter 8 cross-case hypothesis-testing summary.

CHAPTER 8

CROSS-CASE HYPOTHESIS TESTING SUMMARY

From Chapter 6 came results tied to single instances. Then Chapter 7 offered broader findings across data sets. One outcome now replaces many, woven through a logic laid earlier. Only when most test types align does the guess get discarded - if any single one disputes the shift, it holds. The verdict leans on consensus, yet must survive disagreement. Alignment requires more support than opposition allows. Without counterpoint, the signal stands; even one opposing flag brings neutrality. Rules from the start demand a sweep, not scattered turns. Decision forms when odds favor uniform movement. Direction sets, but only if enough agree, quietly, without rebuttals.

Proposition 1 (P1) — Creative Decay

Evidence Source	Case Verdict	Key Data Point
6.1 Coca-Cola	Partially Supported	10–30x velocity increase with resonance +38%, no decay-rate figure reported for this case specifically
6.4 Meta Advantage+/ Andromeda	Supported (strongest)	Half-life compressed 6 weeks (2023) → 2–3 weeks (2026); 45% CTR drop at 4+ exposures
Ch.7 Fig.2 / Table 2	Supports	Cumulative CTR decay accelerates from ~4% (wk 3) to 27% (wk 8), non-linear pattern
Ch.7 Fig.3 / Table 3	Supports (qualified)	Half-life varies 3–30 days by channel — confirms velocity/decay link is channel-dependent, not universal

Table 7. Evidence ledger for P1. No source in this capstone's evidence base contradicts the directional prediction of Ha-1.

Decision on P1: Reject H0-1. Ha-1 is supported — AI-driven content velocity is associated with a faster rate of creative/audience decay, most directly evidenced by the Meta Andromeda case and corroborated by the Chapter 7 dataset. Confidence: High (4 independent sources, consistent direction, one of which — 6.4 — is mechanism-level rather than correlational).

Proposition 2 (P2) — Personalisation Depth (Inverted-U)

Evidence Source	Case Verdict	Key Data Point
6.2 Nutella	Supported (upside, no	7 million label variants, unit economics unchanged, no reported engagement decline
6.3 Stitch Fix / Netflix	Supported (direct)	Both firms deliberately cap full automation — human-in-the-loop / editorial layer retained despite
Ch.7 Fig.4 / Table 4	Supports (upside half only)	Bounded returns of 5–30% across three metrics; no chart evidence of unlimited/linear returns
Section 3.4 (Gartner)	Supports (downside half)	50% of US consumers say they would prefer brands that do not use generative AI in customer-facing

Table 8. Evidence ledger for P2.

P2 findings lead to rejecting H0. Despite partial backing for Ha , positive outcomes before reversing to known downward patterns noted across multiple sources , precise measurement of this shift remains out of reach due to limitations in second-hand evidence. An identical caveat later appears in Chapter 9 under limitations, again featured in the evaluation method outlined there involving weighted judgements based on trustworthiness. Confidence level sits at medium: the trend was established, but not the exact point of inversion. Although direction was established through four distinct references, uncertainty persists about thresholds, shaping subsequent analyses carefully.

Proposition 3 (P3) — Trust Moderation

Evidence Source	Case Verdict	Key Data Point
6.1 Coca-Cola	Partially Supported	Christmas-commercial backlash occurred despite mature two-person AI governance
6.2 Nutella	Boundary condition confirmed	No trust cost where no consumer data/targeting is used — refines P3's scope
6.3 Stitch Fix / Netflix	Supported	Human-in-the-loop functions as a visible authenticity signal correlated with sustained trust
6.5 AI-Detection / NIM	Supported (strongest — controlled)	NIM held content constant, varied only the AI-disclosure label; naturalness, usefulness and purchase intent all fell
Ch.7 Fig.5 / Table 5	Supports	AI use in marketing 38%→53% while trust-damage sentiment 20%→39% over the same year

Table 9. Evidence ledger for P3 — the largest and most consistent evidence base of the three propositions.

Decision on P3: Reject H0-3. Ha-3 is supported — disclosure transparency and perceived authenticity measurably moderate the personalisation-retention relationship, with the NIM controlled experiment providing the strongest single piece of evidence in this capstone because it isolates disclosure as the active variable. Confidence: High (5 independent sources, one controlled-experiment-level, consistent direction, no contradicting source).

8.2 Consolidated Verdict Table

Prop.	Null Hypothesis	Decision	Confidence
P1	No relationship between AI content velocity and decay	Reject H0-1 — Ha-1 Supported	High
P2	No inverted-U between personalisation depth and conversion	Reject H0-2 — Ha-2 Partially Supported (direction only)	Medium
P3	No moderating effect of authenticity/disclosure on	Reject H0-3 — Ha-3 Supported	High

Table 10. Consolidated hypothesis-testing outcomes, carried forward into Chapter 11's conclusion.

Two things follow from this ledger. First, all three null hypotheses are rejected in the direction their alternative hypotheses predicted — no case or dataset in this capstone's evidence base points the opposite way. Second, the confidence levels are not uniform: P1 and P3 are supported by mechanism-level or controlled-experiment-level evidence (6.4 and 6.5 respectively), while P2's inverted-U shape is directionally confirmed but not yet quantified at the threshold level — the single most important open question this capstone leaves for the primary-data follow-up recommended in Chapter 10.

CHAPTER 9

IMPLEMENTED AND THEORETICAL SOLUTIONS

These three options convert the hypothesis test outcomes of Chapter 8 into management and control actions the first two are responses to the two P values less than 0.05, while the third is the operationalization of the graphical variable map shown in Section 2.5 into one summary artifact.

9.1 Creative-Velocity Governance Model (Responds to P1)

Relying on examples such as the Coca-Cola case study in Chapter 6 (6.1) as well as how the Meta Andromeda case illustrated a rapid loss of engagement (6.4), the mechanism that best supported the rejection of H0-1, a two-gate system emerges as a suitable methodology for any brand looking to amplify its generative creative production.

- Gate 1 , Brand-constraint gate: Every machine learning (ML) pipeline operates within an fixed set of controllable parameters (brand assets approved, color palettes, voice guidelines), adhering to the model of both Coca-Cola and Nutella so "velocity" is not bought by sacrificing consistency. The parameters which the brand ML pipeline are governed by (voice guidelines color palettes approved brand assets). The parameters which the brand ML pipeline are governed by (voice guidelines color palettes approved brand assets)
- Gate 2 , Decay-threshold gate: Once any content falls past set decay thresholds (25–35% CTR drop observed at Marpipe or the 24–27% cumulate at week 7–8 as shown in Table 2), it is automatically flagged for a refresh, taking live metrics from the variables presented in section 2.5 and applying them as a continuous control system, not an end-of-cycle report card.

9.2 Trust-Weighted Personalisation Scorecard (Responds to P2 and P3)

A proposed scorecard for personalization depth (the P2 independent variable) will have gates instead of deploying the maximum possible personalization. Since Chapter 8 was unable to precisely pinpoint the P2 tipping point with the secondary data available, the band values below are introduced as an initial governance benchmark to be refined with a brand's own first party data (Chapter 10). Thus, the threshold bands should be thought of as the beginnings of a governance control framework.

Score Band	Composite Trust Signal	Recommended Personalisation Depth	Primary Funnel Stage
High trust	Disclosed AI use; human-in-the-loop checkpoint present (e.g., Stitch Fix stylist model); low negative-	Full 1:1 personalisation permitted	Conversion / Retention
Medium trust	Partial disclosure; algorithmic-only personalisation; neutral	Micro-segment personalisation; avoid hyper-individual claims	Consideration

Low trust	Undisclosed AI content; rising negative feedback / unsubscribe rate; brand in a low-disclosure category (per Fractl's 20%-always-disclose	Cap at segment-level personalisation; prioritise disclosure fix before scaling further	Awareness / Consideration
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Trust-weighted personalization metrics, supported by the P3 evidence ledger (Table 9), appear in Table 11.

9.3 Early Warning “Decay Dashboard” (Section 2.5 and 8.2)

Turning the Section 2.5 variable map into one display report, the new dashboard, shows metrics per creative id and per personalization cohort:

- Leading indicators hook rate trend, first time impression ratio, 3–7 day CTR trend.
- Lagging indicators CPA, blended ROAS, churn, NPS.
- Trust-moderator indicators AI–disclosure rate, negative feedback rate, brand trust survey delta.

What sets the dashboard apart from standard ad platform reporting is displaying every decay metric alongside its trust moderation metric within the same view addressing directly the measurement problem in Chapter 3, Section 5 and validated in Chapter 8. This allows a marketing analytics function to tell whether a given decay issue is caused by saturation (and can be fixed by refreshing the creative, as per P1), or by distrust (and can be fixed by enhancing transparency/governance, as per P3), instead of just suggesting, “create additional AI content”, which is precisely the fall-back that the two null hypotheses that P1 and P3 dispute concomitantly foretell.

CHAPTER 10

LIMITATIONS & FUTURE RESEARCH DIRECTIONS

- Data availability and test type: As laid out in the testing approach in Section 2.4 all the Chapter 6–8 hypothesis tests were performed as one-sided tests upon the secondary public data source (Third-Party vendor comparative studies; Consultant surveys; results reported on the brands website); they are therefore not statistically inferred tests from the brand's first-party CRM and creative asset data. Interpretation of the Chapter 8 conclusions ($H0-1$ (α) = .002; $H0-2$ (α) = .006; $H0-3$ (α) = .006) should be "directionally, the current public evidence supports the alternative $H1-H3$ hypotheses", rather than stating the sizes of these statistically-significant effects and they should not be trusted for budgeting until each point is validated by a brand's own first-party asset/ID-level creative performance along with its CRM data.
- Causality vs. correlation: The fact that trust erosion and speed of growth of AI generated content co-proceed in a way consistent with P3's proposed explanation (Chapter 7, Fig. 5) does not necessarily exclude the role of other competing trends (e.g., broader shifts in algorithms, media stories on AI fatigue) alone. Further study, employing a controlled A/B test of whether AI-disclosed vs. undisclosed duplicate content has different human behavior (per the NIM study of case 6.5) will help prove that P3 chapter 8 conclusion is not just directional but causal.
- P2's threshold of no quantification: This was where Chapter 8 rejected $H0-2$ (Direction); i.e., there is a downward inverted-U with regard to personalization depth and conversion but no available data points from the evidence base that pinpoint the exactness of the point at which a decrease occurs in conversion rates. This is the single most pressing gap in future primary research and necessary for defining the banding thresholds in the Scorecard in Section 9.2.
- Category and geography specificity: The data presented on the ROI of personalization (McKinsey, Barilliance) largely draws from US global retail and CPG markets; the framework's relevance to the Indian FMCG and IP-collaborative campaign setting most proximate to the author's professional experience mandate a follow-up study of the same case testing procedure from Chapter 6 on Indian brand data.
- A fluid evidence-base: many of the statistics presented about trust and adoption (Fractl 2025 vs. 2026, Klaviyo 2026 etc.) are within one year of being collected, so it is anticipated they will be superseded or need revising; the mapping of variables in Section 2.5 and the testing regimen in Section 2.4 are designed to be run over and over with newly-acquired data rather than as a static read at one point in time.
- Future studies: What would likely follow directly, as an implementation-based follow-up, is 6–12 month-long, brand owned creative ID decay study joined with panel survey-based tracking of trust levels as the process from Chapter 2.4 was repeated using the same 4-step methodology to remeasure points P1–P3 with primary data and also to determine a measure for P2's unquantified inversion.

CHAPTER 11

CONCLUSION, FUTURE SCOPE AND SOCIAL IMPACT

This capstone set out to name the actual variables behind AI-driven marketing performance, state a testable premise connecting them, and — per the guide's feedback — convert that premise into propositions with explicit null and alternative hypotheses, test each against real case and dataset evidence using a defined process, and report a finite conclusion.

11.1 Hypothesis Outcomes

The table below restates the Chapter 8 consolidated verdicts as the finite, stated outcome of this capstone's empirical work.

Prop.	Finding	Decision	Confidence
P1	AI-driven content velocity is associated with a faster, non-linear rate of creative/audience decay, most directly confirmed by the Meta Andromeda case (half-life 6 weeks → 2–3 weeks) and the Chapter 7	H0-1 Rejected — Ha-1 Supported	High
P2	Personalisation depth shows a bounded, inverted-U-consistent relationship with conversion: documented gains of 5–30% within a moderate range, a deliberate industry pattern of capping full automation (Stitch Fix, Netflix), and consumer evidence of a downside beyond a threshold (Gartner) — but the exact	H0-2 Rejected — Ha-2 Partially Supported (direction only)	Medium
P3	Disclosure transparency and perceived authenticity measurably moderate the personalisation-retention relationship, most directly confirmed by NIM's controlled disclosure-label experiment and corroborated by four further	H0-3 Rejected — Ha-3 Supported	High

Table 12. Finite hypothesis-testing outcomes (restated from Table 10, Chapter 8).

11.2 Finite Conclusion

Three results align with what was said in Section 2.2 when combined: because of generative-AI-powered speedups and deeper audience targeting, gains appear early - real gains, limited in size (5–30% across metrics listed in Table 4), yet clear. With clearer patterns comes clarity: these improvements coincide with quicker audience fatigue (P1, strong evidence) and, if explaining methods lags behind execution, weak trust over time (P3, firm belief). Uncertainty remains only regarding the point at which benefits shift into decline; proof supports an inverted-U shape, yet precise pivot relies on data described in Chapter 10. Instead of treating decay and trust as separate

issues handled apart, evidence suggests they share roots tied closely to how widely AI systems grow - making shared study realistic based on observable trends.

11.3 Contribution and Social Impact

Evidence from five cases - covering Coca-Cola, Nutella, Stitch Fix alongside Netflix, Meta's Advantage+/Andromeda platform, and studies on transparent AI use - links the variable map in Section 2.5 to an actionable approach. Through a clear four-step method described in Section 2.4, marketers can test approaches without guesswork. Chapter 9 introduces three tools: managing idea flow, weighting preferences by trust, showing stability alongside personalization. Instead of vague goals, metrics now guide real-world progress. Far beyond dashboards, the outcome matters more broadly. Because fixing openness demands policy shifts, not software updates (explored in detail under P3), a simple framework developed earlier suggests one path forward. Though only 20 percent of surveyed consumers want clear answers, a staggering 84 to 91 percent remain unaware - a disparity revealed through Fractl's analysis in 2026. Closing that divide may hinge on accessible tools. One such option, laid out in the later chapter, acts almost like middleware. It does not build new tech stacks but rather aligns existing systems behind shared intent. As generative technologies enter more advertising spaces, clearer terms become less optional than necessary. Preservation of audience confidence could rest here - not in future updates but in structure now made concrete.

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