A Forensic AI Audit Framework for Digital Marketing Funnel Performance and ROI Protection

AMA WINTER CONFERENCE 2026
MADRID, SPAIN

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UNIVERSITY of DENVER

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We Make Claims Because We Have Built the Technology

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AI Auditing + Cybersecurity is Foundational

*Despite the growing influence of AI-mediated technologies, **marketers lack mechanisms to verify whether AI systems are executing strategy accurately or optimizing digital spend** (Viitanen, 2025; Mittelstadt et al., 2016).*

AI Has Outpaced Visibility

- AI systems now mediate discovery, messaging, and conversion
- Decisions occur inside opaque, black-box environments (Pasquale, 2015; Raji et al., 2020, Diakopoulos, 2016)
- Leaders see outcomes—but not causes
- Accountability breaks when systems cannot be observed (Altundag, 2025)

What search taught us about invisible optimization risk is now accelerating in AI-mediated environments.

Deeper

Faster

with Higher Stakes

Why AI Risk Compounds at Scale

- IP exposure
- Black-box decisions
- Full Charged | ½ or less delivery
- Misalignment to objectives
- Inconsistent reproduction
- Costly optimization errors
- Scaling without governance
- Layered autonomy amplifies error
- Signal interactions increase unpredictability
- Multiple points of interference
- Multiple ways to hallucinate, creep, redirect
- Governance lags behind system complexity

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Signal Is the New Attack Surface

The Strategy Question

Can one see in the background, in the black-box of activity to determine if what I think is happening is really happening?

Can AI be audited to mitigate risk?

The Strategy Realized

First Step, Forensics & Diagnostics

Designed around 36+ proven theories and frameworks proven in the digital purchase analysis.

- *Audit-by-Output (Bolin & Andersson Schwarz, 2015; Hoque & Mueller, 2021; Pasquale, 2015)*
- *Behavioral Malfunction (Chen et al., 2024; Mahlangu et al., 2025; Viitanen, 2025)*
- Decision Traceability (Diakopoulos, 2019; Pasquale, 2015; Lin et al., 2024, Viitanen, 2025)
- Funnel Integrity (Jurafsky & Martin, 2020; Lemon & Verhoef, 2016; Saadallah et al., 2024)
- Predictive Modeling Risk (Chen et al., 2024; Lin et al., 2024; Sánchez & Bellogín, 2022)
- Systems Theory of AI (Cody et al., 2020)
- Nudge Theory / Choice Architecture (Thaler & Sunstein, 2008)
- Stochastic Consumer Behavior (Kannan & Li, 2017)
- Algorithmic Opacity Typology (Burrell, 2016)

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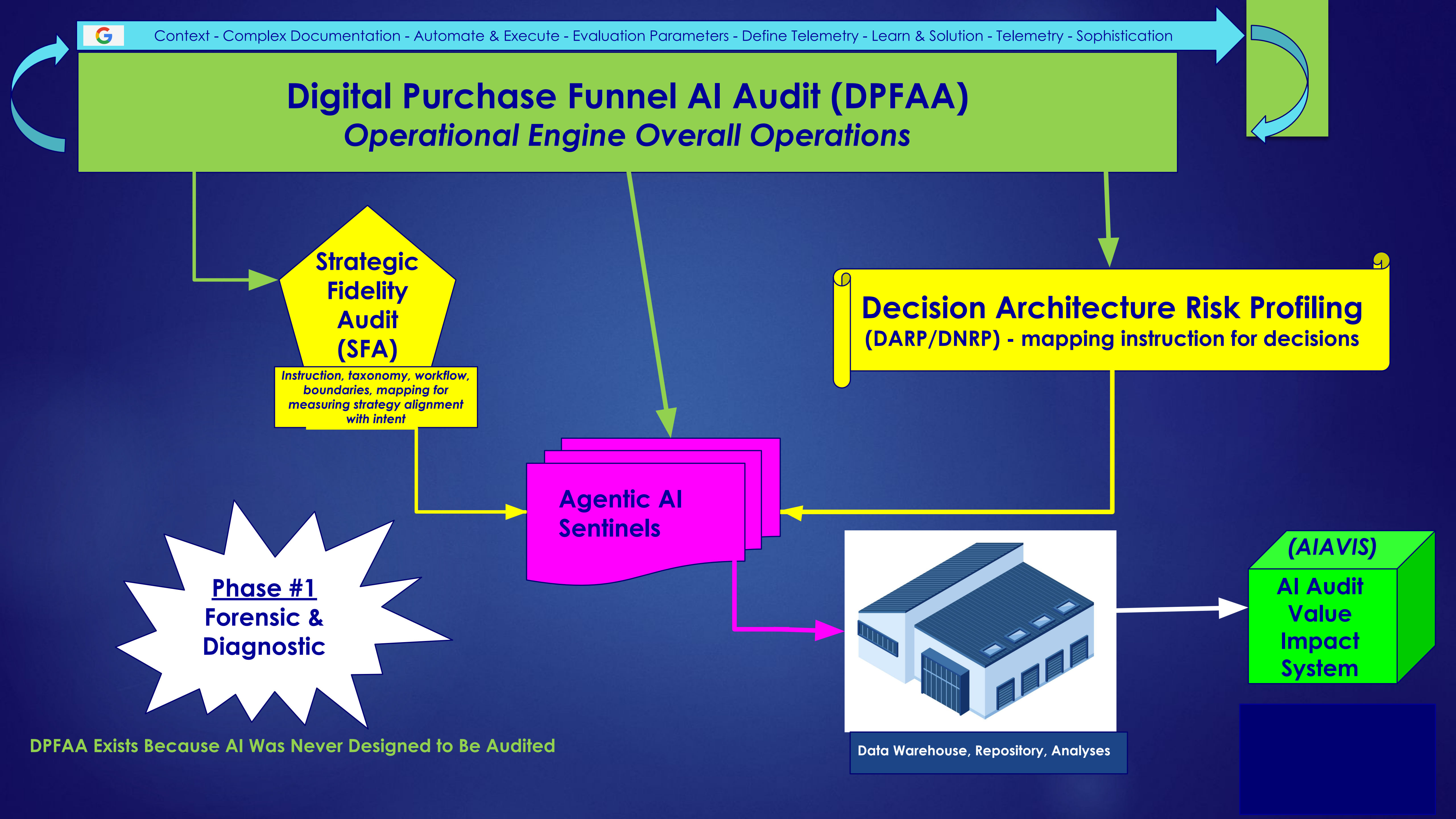

Context - Complex Documentation - Automate & Execute - Evaluation Parameters - Define Telemetry - Learn & Solution - Telemetry - Sophistication
Digital Purchase Funnel AI Audit (DPFAA)
Operational Engine Overall Operations
Strategic Fidelity Audit (SFA)
Instruction, taxonomy, workflow, boundaries, mapping for measuring strategy alignment with intent
Decision Architecture Risk Profiling
(DARP/DNRP) - mapping instruction for decisions
Agentic AI Sentinels
Phase #1
Forensic & Diagnostic
Data Warehouse, Repository, Analyses
(AIAVIS)
AI Audit Value Impact System
DPFAA Exists Because AI Was Never Designed to Be Audited

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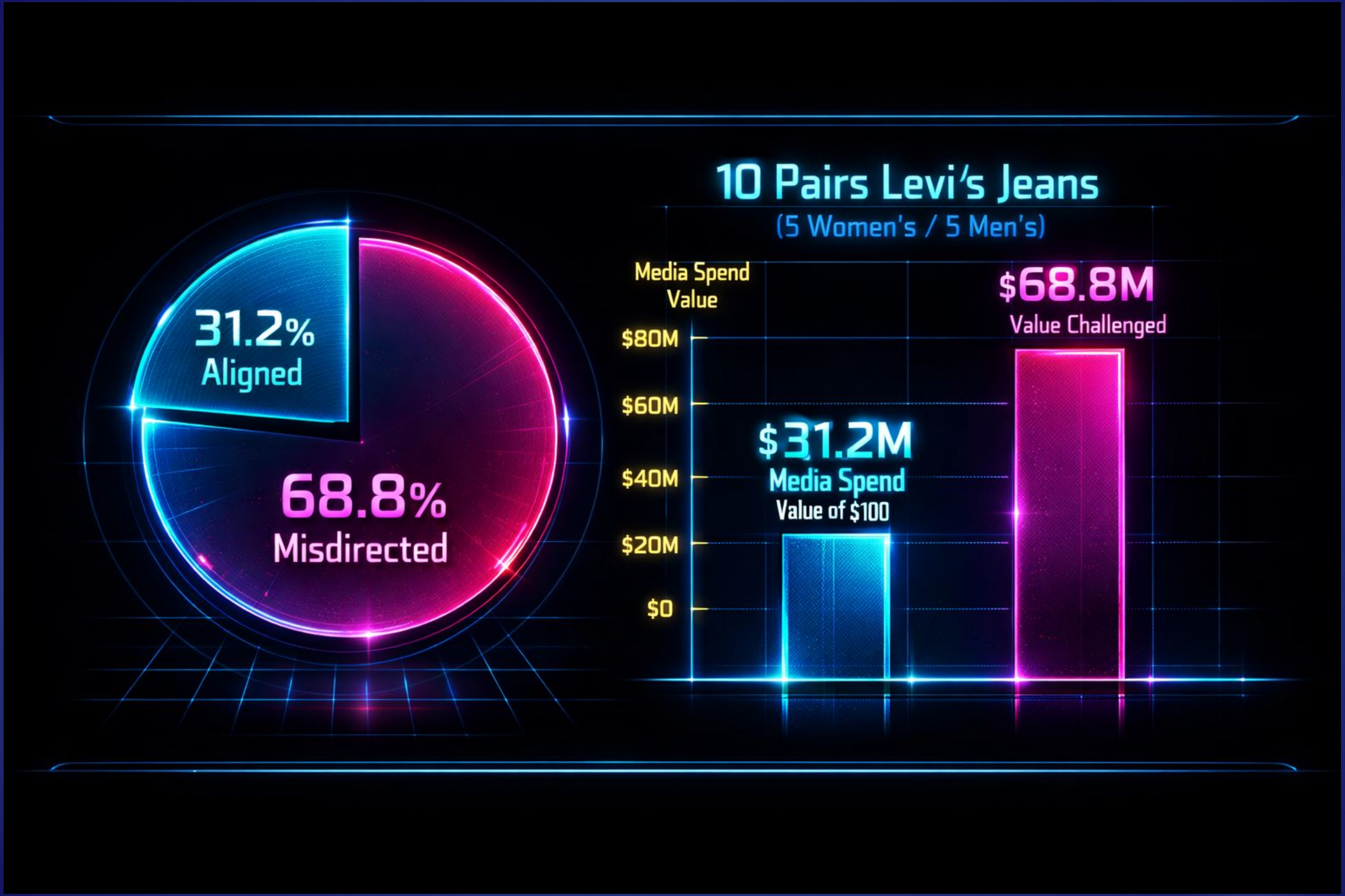

Why DPFAA Works

- Combines theoretical analysis with empirical outcome verification
- Agentic AI (ChatGPT, Claude, Gemini), GitHub, Supabase, Railway
- Overlays proven frameworks, taxonomies, and models onto AI-mediated systems
- Boundaries & mapping
- Uses audit-by-output as one layer, not the sole method
- Independent adjudication restores accountability without requiring internal access

How Agent Interfaces are Layered

Google

6 Core Components of an Agent Interface

Note by Will Gannis, CTO, Google Cloud

- Chat Interface
- The Model Fills in the Intelligence
- Agent Platform Task Automation
- Out-of-the-box Agents
- Connectors Grab Third-Party Data
- Governance & Security

AI Auditing Opportunity

(CXOTalk, 2026)

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Every Build is Iterative

(CXOTalk, 2026)

The DPFAA Workforces Agent Alignment with Google

01

CONTEXT

- Intervention archetypes
- Algorithmic Influences by agent
- Types of AI-mediated responses

02

COMPLEX DOCUMENTATION

- Organizing framework mapping
- Mapping types of Influences at stages

03

AUTOMATION & EXECUTION

- Writing LLM Instruction for Collection and repository deposits

EVALUATION PARAMETERS

- Defining types of calculations
- Developing Indexing
- Statistical analysis

04

DEFINE TELEMETRY

- Longitudinal tracking of drift
- Record behavior across sessions, users, and time windows

05

Documentation Process & Boundary Setting

(CXOTalk, 2026)

Agents Search, Collect Data, Deposit in Repository, & Calculate Results

Marketing Implications

- Lemon and Verhoef (2016) deviations in customer journeys serve as behavioral indicators of algorithmic interference rather than simple campaign failure. How is this diagnosed?
- Rust (2021a) AI systems do not merely observe behavior but actively shape it, blurring the boundary between analytics and persuasion. What are the forensics?
- Behavioral auditing must evolve into strategic diagnostics, capable of revealing when system-led optimizations distort brand messaging, consumer perception, or return on investment (Lemon & Verhoef, 2016; Rust, 2021a). How do we track this?
- Deviations in funnel flow, suppressed visibility, rerouted journeys, altered decision timing, or reframed content can signal system-level interference (Diakopoulos, 2019). How do we see this?
- Yet traditional analytics platforms remain largely blind to these dynamics. This condition produces what Altundağ (2024) terms an auditability gap: a blind spot in which marketers observe outcomes without the ability to trace how or why those outcomes were produced.
- Addressing this gap requires shifting from performance dashboards *to funnel integrity auditing*, evaluating whether observed journeys remain aligned with declared strategic intent or have been reshaped by autonomous system priorities (Rust, 2021a; Raji et al., 2020).

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What’s Coming Up

Research Needing Funding

- DPFAA - Next Generation
- AIAVIS - B2B AI Auditing
- AIAOE - The audit engine

Appointment Calendar

Scan to schedule a consultation appointment to find out more.

Products & Services Available

- Baseline Proof of Concept (POC) Services
- Customized POC
- Customize DPFAA Workforce Agent

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Presentation

Thank You!

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