

AI and the Transformation of Advanced TV and Video Advertising and Media Measurement

From Workflow Automation to
Agentic Market Infrastructure

October 2026





About CIMM

The Coalition for Innovative Media Measurement (CIMM) brings industry participants together to improve media measurement, currency development, metrics and data collaboration. Its members work across the systems that support the media and advertising market.

CIMM's work is grounded in the belief that durable progress in media measurement requires collaboration across the full ecosystem: publishers, agencies, advertisers, platforms, measurement providers, technology companies, identity providers, data providers, and other market participants.

AI makes that collaboration more consequential as it begins to shape the systems these organizations share.

This paper was authored by **Jon Watts, Managing Director of CIMM.**

Foreword

The U.S. TV and video advertising market is entering a new phase of AI adoption. AI is moving beyond isolated workflow automation into planning, activation, measurement, optimization and commercial decision-making across advanced TV, CTV, streaming and programmatic video. This paper examines current applications across creative development, planning, audience construction, activation, measurement and optimization. Its focus is the point at which AI ceases to be a company-level productivity tool and begins to shape shared workflows, interfaces and decision rights across the market.

This matters because advanced TV and video advertising depend on shared systems of trust. Measurement, currency, identity, audience definition, inventory classification, data collaboration, reach and frequency management, attention, quality, and outcome accountability are not simply company-specific product categories. They are market infrastructure. When AI begins to interact with these systems, it has implications not only for productivity, but for transparency, comparability, pricing power, inventory packaging, stewardship, governance, and commercial accountability.

CIMM's first Innovation Showcase paper of 2026, Identity Infrastructure 2.0, examined identity resolution in U.S. TV and CTV. CIMM's second 2026 Innovation Showcase, held June of 2026, was focused on AI's growing role in the market's shared workflows and systems. This report draws on presentations and discussions from this June AI Innovation Showcase, subsequent stakeholder discussions, and related CIMM work on marketing mix modeling, media quality, identity infrastructure and data collaboration. Participating industry leaders supplied the frameworks, case studies, quantitative evidence and perspectives examined here.

The Showcase included production capabilities, pilots and demonstrations spanning creative generation, brief-to-plan workflows, audience construction, measurement-data mapping, campaign diagnostics, streaming optimization and agent-to-platform execution. These examples indicate that AI is beginning to coordinate decisions across the advertising lifecycle, although maturity and scale vary by use case.

The report's central argument is that AI will increase the operational importance of measurement, identity, media-quality evidence, data collaboration and governance. The policy question is how to capture the benefits of faster coordination without weakening privacy, competition, commercial choice or accountability.

Jon Watts

Managing Director,
The Coalition for Innovative Media Measurement

October 2026

Research Objectives and Approach

This report represents CIMM's independent analytical synthesis of the presentations and discussions delivered during the June 2026 CIMM AI Innovation Showcase, together with additional industry and academic research.

The interpretations, conclusions, frameworks and recommendations contained in the report are those of CIMM and the author. They do not necessarily reflect the official positions, policies or opinions of any individual contributor, participating company or other organization referenced in the report. Participation in the Showcase, or inclusion in these acknowledgements, should not be understood as endorsement of the report's analysis, findings or recommendations.

Product demonstrations and company case studies are included to illustrate emerging capabilities and market developments. Unless expressly stated otherwise, company-reported results, performance claims and operational examples have not been independently audited or validated by CIMM and should not be interpreted as generally applicable market benchmarks. Demonstrations may reflect pilot programs, beta products, selected use cases or capabilities that are not yet available at full commercial scale.

The report does not constitute legal, regulatory, financial or technical advice. Market participants should undertake their own assessment of the suitability, reliability, privacy implications, governance requirements and commercial risks associated with any AI-enabled system or workflow.



Acknowledgements

CIMM thanks the executives and organizations that contributed to the AI Innovation Showcase on June 3, 2026. Their presentations and demonstrations informed this report.

We would like to acknowledge the important contributions of:

David Dworin, Chief Product Officer, FreeWheel.

Jonathan Moffie, Head of Agentic, Magnite.

Jason Manningham, CEO and Founder, Blockgraph.

Jack Foster, Head of Cross Media Intelligence, LiveRamp.

David Wells, Industry Principal, Media and Advertising, Snowflake.

William Merchan, Industry Principal, Media and Entertainment, Snowflake.

Amanda Carlton, Vice President, Performance Products, DoubleVerify.

Marissa McArdle, Senior Vice President, Streaming TV Product, DoubleVerify.

Karen Nelson-Field, Founder and CEO, Amplified Intelligence.

Hamilton Radcliffe, Head of Product, StationOne and Atlas Performance, Kochava.

CIMM also thanks Noelle Huynh, Senior Vice President of Projects and Strategic Initiatives, for developing and delivering the Showcase and supporting CIMM's AI research program.

Contents

Executive Summary	7
Introduction. AI as the Next Infrastructure Challenge for Advanced TV and Video	12
Chapter 1. From AI Tools to Market Infrastructure	15
Chapter 2. The Emerging AI Stack for Advanced TV and Video	18
Chapter 3. Agentic Buying and the Automation of Market Workflows	21
Chapter 4. Creative-to-Activation: Lowering the Cost of Entry to CTV	28
Chapter 5. AI, Identity, and Real-World Audiences	31
Chapter 6. AI-Powered Measurement and the Shift from Reporting to Optimization	35
Chapter 7. MMM, Outcomes, and AI-Driven Decision Systems	42
Chapter 8. Media Quality, Attention, and Machine-Readable Value	46
Chapter 9. Algorithmic Optimization in Streaming TV	52
Chapter 10. Composable Data Infrastructure for People and Agents	57
Chapter 11. Commercial Models and Institutional Change	62
Chapter 12. Governance, Transparency, and Market Integrity	67
Chapter 13. Conclusion: Building Accountable Market Infrastructure	74
Appendix A. Practical Questions for Senior Executives	75
Appendix B. AI Readiness Checklist for Advanced TV and Video	76
Appendix C. AI Use Case Matrix	78
Appendix D. Sources and References	80

Executive Summary

Artificial intelligence is changing advanced television and video advertising less through any single application than by lowering the cost of coordinating decisions across the campaign lifecycle. Systems can now translate briefs into plans, create and adapt assets, construct audiences, configure campaigns, reconcile measurement data, diagnose delivery problems, recommend optimizations and, within defined limits, execute approved actions. When these functions connect data and systems across organizations, AI moves beyond a productivity tool and becomes part of the market's coordination infrastructure.

The capabilities reviewed span production systems, pilots, beta products and demonstrations. Together, they point to four market developments:

- 1 AI is compressing the campaign lifecycle.** Planning, creative development, activation, delivery management, measurement and optimization are beginning to operate as a continuous feedback system. Human work shifts toward defining objectives, approving material actions, exercising judgment, managing exceptions and retaining accountability. The management question is which decisions may be delegated, within what limits and on what evidence.
- 2 Measurement is becoming operational.** Measurement outputs can influence campaigns while investment remains in flight, allowing evidence to affect decisions before budgets are fully committed. The same connection raises the cost of methodological weakness: an imperfect report may shape one later discussion, whereas an imperfect signal connected to optimization can redirect expenditure repeatedly. Decision authority should reflect the signal's causal strength, uncertainty, freshness and fitness for use.
- 3 Cost, impressions, completion and short-term conversion are comparatively easy to structure for automated use.** Context, exposure environment, attention, co-viewing, incrementality and longer-term brand effects are harder to represent. Systems should use these measures only when the underlying concepts are clearly defined, the methods are defensible and the measures suit the advertiser's objective. A signal's machine-readable format does not establish its validity.
- 4 AI will redistribute market power as well as operational work.** Organizations controlling transaction data, execution environments, identity infrastructure or widely used interfaces may gain influence because external agents depend on access to their systems. Open APIs do not by themselves guarantee meaningful interoperability. Access terms, available data fields, permitted actions, certification requirements, portability and switching costs will shape which participants can compete and which systems can be challenged. The appropriate objective is contestable interoperability: sufficient access and portability to support competition and innovation, combined with proportionate protections for privacy, security, publisher control and contractual rights.

Organizations deploying AI across advanced TV and video should pursue accountable automation: delegate decisions only where AI demonstrably improves a defined workflow or outcome, and apply controls proportionate to the financial value, data sensitivity, reversibility and cross-party consequences of the action. Transparency, privacy protection, commercial choice and clear human accountability should be preserved throughout.

Advertisers, agencies, publishers and platforms should start with bounded use cases. They should identify where AI already influences material decisions, classify the risks, set decision rights and financial limits, and measure results against explicit baselines. Measurement, identity and data providers should document the provenance, methods, uncertainty, freshness and appropriate uses of their outputs. Common technical work should address cross-company problems such as agent identity, permissions, inventory and creative descriptions, action logs, revocation and audit records. Contracts should assign responsibility for unauthorized action, data misuse, disputed performance, system failure and remediation.

Responsibility is distributed. Advertisers must define business objectives and acceptable decision boundaries. Agencies must connect strategy, evidence and execution while managing conflicts among tools, platforms and commercial relationships. Publishers must make inventory and evidence legible without surrendering legitimate control over data and commercial strategy. Platforms must provide secure, scoped and sufficiently portable access to approved functions. Measurement, data and identity providers must document methods, limitations and appropriate uses. Independent assurance should be applied where one party cannot reasonably verify a material claim made by another.

AI increases the speed, scale and operational influence of decisions derived from measurement, identity, media-quality and governance systems. The objective is not maximum automation, but dependable interfaces, trusted evidence and clear decision rights.

An implementation agenda for the market

Industry responses to AI should distinguish between capabilities that individual companies can deploy independently and coordination problems that require common approaches. Not every AI use case requires a new standard or collective institution. Many workflow improvements can be governed through ordinary enterprise controls. Market coordination becomes necessary where agents exchange information across companies, interpret common measurement signals, commit expenditure, represent inventory or create dependencies that affect more than one party.

The discussions during the Showcase highlight six main priorities for industry coordination and collaboration:

1. **Organizations should establish AI-ready data and measurement foundations.** Campaign metadata, exposure definitions, creative identifiers, audience taxonomies, identity assumptions and outcome data should be sufficiently consistent, current and documented for automated use. AI cannot compensate reliably for unresolved ambiguity in the data on which it acts.
2. **Advertisers, agencies, publishers and platforms should define decision rights before delegating material authority.** Governance should specify which systems may advise, configure or execute; which actions require approval; what financial and operational limits apply; and how exceptions are escalated. The appropriate degree of human oversight should depend on the value, reversibility and risk of the decision, rather than on a general preference for either human or automated control.
3. **The market should make commercially relevant value signals usable by both people and systems.** Inventory characteristics, context, attention, brand suitability, reach, frequency, measurement options and outcome evidence should be represented in structured forms when doing so is methodologically defensible. The objective is not to create a universal quality score, but to prevent automated systems from optimizing only against the signals that are easiest to obtain.
4. **Standards initiatives should concentrate on cross-company interoperability and control problems that individual organizations cannot solve independently.** Common approaches may be needed for agent identity, inventory discovery, permissions, campaign configuration, status reporting, audit records and the transmission of measurement context. Standards should establish minimum interoperability and control requirements without determining commercial strategy, pricing or a single optimization methodology.

5. **AI-enabled decisions should be documented, auditable and contestable.** Organizations should be able to determine what data and models informed a material decision, what constraints applied, which system acted, who authorized the action and how the outcome was evaluated. Buyers and sellers will also need contractual clarity regarding error, unauthorized action, data misuse and disputed performance.
6. **The industry should scale AI by expanding from well-defined, bounded use cases that are evaluated against explicit baselines and, when appropriate, subject to independent review.** Early deployment should prioritize workflows where objectives are clear, actions are reversible and performance can be compared with the process being replaced. Evaluation should examine not only efficiency and campaign outcomes, but error rates, distributional effects, privacy performance, human intervention and unintended consequences.

Responsibility is distributed. Advertisers must define business objectives and acceptable decision boundaries. Agencies must connect strategy, measurement and execution while managing conflicts among tools and platforms. Publishers must make inventory legible without surrendering sensitive data or commercial control. Platforms must provide secure, scoped and portable access to functions. Measurement, data and identity providers must document methods, uncertainty and fitness for use. Standards bodies can address interoperability, while contractual arrangements and enterprise governance will remain the principal mechanisms of accountability.

Definitions

Artificial Intelligence

A broad class of computational systems that identify patterns, generate outputs, support decisions, automate workflows, optimize toward defined objectives, or interact with external systems. In this paper, AI refers not only to generative AI, but also to predictive modeling, machine learning, optimization algorithms, natural-language interfaces, and agentic systems.

Predictive AI

AI systems that use historical data, statistical models, and machine learning techniques to forecast outcomes, classify signals, detect patterns, or optimize against known objectives. Examples include forecasting models, audience models, pacing algorithms, bid optimization models, and anomaly detection systems.

Generative AI

AI systems that create new outputs, including text, images, video, synthetic creative variants, metadata, campaign plans, audience descriptions, recommendations, and analytical summaries. In advertising, generative AI is increasingly used in creative development, campaign planning, translation, personalization, and reporting.

Agentic AI

AI systems capable of interpreting goals, planning steps, invoking tools, interacting with external systems, and taking action within defined parameters. Agentic systems may recommend actions, execute changes, coordinate workflows, or operate across multiple platforms, depending on the permissions and constraints established by human users or enterprise governance systems.

Agentic Buying

The use of AI agents to support or execute parts of the media buying process, including interpreting briefs, generating plans, discovering inventory, configuring campaigns, creating orders, negotiating terms, pacing delivery, optimizing spend, and reporting outcomes.

Agentic Measurement

The use of AI agents to ingest, map, reconcile, analyze, interpret, and act on measurement data. Agentic measurement moves beyond reporting what happened and toward helping determine what should happen next.

AI Infrastructure

The underlying technical, data, governance, and workflow architecture that allows AI systems to operate reliably across planning, activation, measurement, optimization, and trading. AI infrastructure includes data foundations, APIs, identity systems, clean rooms, workflow orchestration, model governance, permissions, audit trails, and shared definitions.

Machine-Readable Media Quality

Quality, attention, context, placement, or exposure-environment signals structured in a way that AI systems can ingest and use as planning, bidding, optimization, or measurement inputs.



Measurement-Grade AI

AI-enabled measurement systems that are transparent, auditable, interoperable, and sufficiently governed to support planning, optimization, reconciliation, and accountability in commercial decision-making.

Human-in-the-Loop and Human-on-the-Loop

Human-in-the-loop describes a workflow in which human users retain review, approval, exception-handling, or decision authority over AI-generated recommendations or actions. Human-on-the-loop describes a workflow in which AI systems execute actions autonomously within defined parameters, while human users monitor performance, set strategy, supervise governance, and intervene when exceptions or escalation triggers occur.

Introduction.

AI as the Next Infrastructure Challenge for Advanced TV and Video

Advanced TV and video advertising is becoming more fragmented, automated and data-dependent. Viewing now spans linear television, connected TV, streaming services, FAST channels, addressable TV, digital and social video, retail media, and platform-controlled ecosystems. Advertisers want more reliable ways to understand reach, frequency, attention, incrementality and business outcomes across these environments. Publishers and platforms are seeking to protect the value of premium video while adapting to increasingly automated and performance-oriented buying. Agencies are redesigning planning, activation and reporting workflows, while measurement providers face growing pressure to make data faster, more interoperable, more transparent and more actionable.

AI can reduce coordination costs across fragmented systems by translating briefs into campaign parameters, mapping taxonomies, identifying audiences, classifying content, generating creative variants, interpreting results and recommending or executing approved optimizations.

The same coordination capacity can amplify existing weaknesses. Measurement, identity, media-quality and data-collaboration foundations remain uneven; linear and streaming systems use different technical assumptions; identity signals vary by environment; outcome measurement remains contested; and premium video value is not always represented in forms automated systems can interpret. Acting quickly and repeatedly against incomplete data, narrow objectives or opaque assumptions can make those weaknesses operational.

Models and agents embedded in planning, buying, selling, measurement and optimization depend on shared definitions, interoperable interfaces, identity assumptions, measurement evidence, permissions and controls. Capability must develop alongside the institutional, evaluation and data infrastructure required for responsible use (Sajadieh *et al.*, 2026, p. 2).

AI as a coordination layer

Advanced TV and video already depends on coordination among advertisers, agencies, publishers, distributors, platforms, identity and data providers, measurement companies, clean rooms and technology vendors. Each participant controls only part of the workflow and operates with different incentives, datasets, definitions and systems.

AI can become a coordination layer across this ecosystem. It can connect planning, creative, activation, measurement and optimization in a more continuous process, allowing information and decisions to move across systems with less manual translation. But this shift also creates new dependencies. Buyers may rely on seller systems to describe inventory accurately; agents may rely on measurement providers for decision-grade evidence; platforms may control access to execution functions; and advertisers may delegate authority through contractual and technical controls.

A tool helps one organization complete a task. Infrastructure governs how organizations interact through shared functions, interfaces, definitions and evidence. AI enters that role when proprietary models and agents need common inputs and rules to coordinate activity across the market.

The objective should be accountable automation: faster and more adaptive decision-making without sacrificing measurement integrity, privacy, competition, commercial choice, auditability or the ability to challenge a disputed outcome. Controls should follow the function being performed, the authority delegated and the consequences of error.

Scope, questions and analytical approach

This paper examines how AI is changing advanced TV and video advertising and media measurement in the United States. It is intended for senior executives across the ecosystem, including advertisers, agencies, publishers, platforms, measurement and data providers, identity companies, clean rooms, cloud platforms and advertising technology providers.

It addresses four questions:

- How is AI changing the operating architecture of advanced TV and video advertising and media measurement?
- What practical innovations are emerging across planning, creative, activation, measurement, optimization and data infrastructure?
- How could AI reshape commercial workflows, decision authority and the roles of key market participants?
- What technical, measurement and governance foundations are needed to support transparency, accountability, competition and the value of premium video?

Exhibit: Analytical frameworks used in this report

Level of analysis	Analytical tool	Purpose	Principal location
Operating architecture	Five-Layer AI Stack	Identifies the signal, intelligence, workflow, execution and governance capabilities that must work together	Chapter 2
Decision governance	Delegation Model	Assesses how much authority AI should receive based on the materiality, risk and reversibility of an action	Chapter 12
Organizational implementation	AI Readiness Checklist	Tests whether objectives, data, measurement, controls, people and processes are ready for a proposed use case	Appendix B

The Five-Layer AI Stack describes the operating architecture. The Delegation Model sets the appropriate level of decision authority. The AI Readiness Checklist applies both to a defined use case.

Exhibit: AI Innovation Across the Advanced TV and Video Lifecycle

Area	Illustrative applications	Immediate value	Enabling requirement
Creative	Video generation, storyboarding, localization and format adaptation	Faster, lower-cost production of variants	Brand controls, rights management and quality assurance
Planning and audiences	Brief ingestion, forecasting, publisher allocation, audience and trade-area creation	Faster planning and broader scenario evaluation	Comparable inventory and audience metadata; reliable identity and privacy controls
Activation and orchestration	Batch campaign creation, agent-to-platform interaction and governed execution	Less manual setup and faster launch	Secure connectors, authenticated agents, scoped permissions and approvals

Area	Illustrative applications	Immediate value	Enabling requirement
Measurement	Data mapping, refresh, quality assurance and results interpretation	Faster preparation and more actionable analysis	Connected exposure and outcome data, transparent methods and common taxonomies
Optimization	Pre-bid and in-flight optimization against reach, quality and outcomes	More continuous allocation and performance improvement	Credible KPIs, comparable reporting and sufficient decision signals
Attention and media quality	Conversion of creative and placement characteristics into structured signals	Earlier assessment and richer optimization inputs	Validated models, appropriate ground truth and platform-specific calibration
Data infrastructure	Semantic layers, clean rooms, composable data and agentic control planes	Governed use of distributed data by people and agents	Ontologies, policies, APIs, collaboration controls and audit logs

Evidence and interpretation

The paper draws on product demonstrations and case studies presented by participating companies at CIMM's AI Innovation Showcase, as well as on published industry and academic research, and original analysis of the possible market consequences of these developments.

These forms of evidence serve different purposes and should not be conflated. A demonstration establishes that a capability can be performed, but not necessarily that it is reliable, scalable or superior across the market. Company-reported campaign results may illustrate potential value but should not be treated as general benchmarks unless independently validated. Conclusions about agentic buying, market structure and institutional change are presented as reasoned scenarios, not forecasts of an inevitable outcome.

The report uses five evidence categories:

- **Independently validated evidence:** peer-reviewed, audited or independently replicated findings.
- **Published industry research:** documented research with methods and samples available for assessment.
- **Company-reported results:** performance claims supplied by a participating organization but not independently audited by CIMM.
- **Demonstrated capability:** a product demonstration or operational example showing that a workflow can be performed.
- **Forward-looking scenario:** an analytical inference dependent on future adoption, interoperability or institutional change.

These labels describe the status of the evidence, not the overall quality of a company or product. Throughout the report, the analysis also distinguishes among capabilities operating in production, capabilities being tested in pilots, and longer-term implications that require wider adoption or institutional change.

Chapter 1.

From AI Tools to Market Infrastructure

Advanced TV and video already spans linear television, CTV, FAST, addressable TV, programmatic and direct-sold video, social video and retail media. These environments increasingly appear in the same planning process but remain divided by technical, commercial and measurement architectures.

Initial AI adoption has focused on task automation: summarizing reports, generating creative assets, forecasting delivery, identifying anomalies, writing metadata, improving bidding and simplifying software. These uses reduce friction in complex workflows.

AI becomes infrastructural when it begins to shape how audiences are defined, briefs are translated into plans, inventory is evaluated, delivery is managed, measurement is interpreted and budgets are reallocated across organizational boundaries.

This distinction is structural. A tool helps a user complete a task; infrastructure shapes the conditions under which multiple participants interact. If AI merely makes reporting faster, its effects remain comparatively bounded. If it influences which inventory is considered, which outcomes are valued and how expenditure is allocated, its consequences extend to market access, bargaining power, accountability and competition.

Adoption remains uneven. In a July 2026 survey, 49% of senior planning and analytics decision-makers at U.S. brands and agencies reported consistent, scaled use of AI in advanced measurement, and 27% reported value from more limited proofs of concept. Scaling was more common among analytics respondents (69%) than planning respondents (30%). General-purpose AI tools were used by 83% of planning teams, while 44% of analytics respondents and 26% of planners reported using AI-agent platforms (IAB & BWG Global, 2026, pp. 12–16).

“This feels like the early days of the internet in terms of its transformative potential. There is still a significant disconnect between where many everyday workflows are today and where this technology is taking us.”

David Dworin, Chief Product Officer, FreeWheel

Why advanced TV and video are uniquely exposed to AI-driven change

Advanced TV and video are especially exposed to AI-driven change because they sit at the intersection of three market transitions:

1. TV and video are moving from relatively standardized linear workflows into a fragmented cross-platform environment. Linear television remains important, but it now operates alongside CTV, streaming, FAST, addressable TV, platform-controlled environments, and programmatic video. Each environment has different signals, different identifiers, different ad-serving logic, different measurement constraints, and different commercial practices.
2. The market is trying to combine the strengths of television with the expectations of digital advertising. Advertisers still value TV for reach, quality, trust, sound and motion, cultural impact, attention, brand effects, and full-funnel contribution. At the same time, they increasingly expect addressability, flexibility, optimization, outcome measurement, faster reporting, and more granular accountability. Advanced TV must satisfy both sets of expectations.
3. TV advertising has historically depended on shared market conventions: measurement currencies, audience definitions, trading norms, stewardship rules, and trusted intermediaries. Digital advertising, by contrast, has often developed through more fragmented proprietary platforms. Advanced TV inherits both traditions. It needs the accountability and automation of digital, but it also needs the trust and comparability associated with TV measurement and currency.

Product innovation versus infrastructure innovation

Much of what the advertising market calls innovation is product improvement. A platform adds a dashboard. A vendor automates a report. A measurement provider adds a model. A publisher offers a new segment. A data provider improves matching. These developments can save time, improve performance, or reduce cost.

Infrastructure innovation is different. It changes how the market coordinates. It affects the rules, workflows, incentives, and shared systems through which participants interact. It influences how value is represented, how trust is established, how transactions are executed, and how accountability is maintained.

AI is moving into infrastructure territory because it can alter decision-making across the advertising lifecycle. Once AI systems begin to read briefs, recommend plans, generate audiences, create campaigns, evaluate inventory, optimize budgets, interpret measurement, and execute approved actions, they are no longer peripheral workflow tools. They become part of the coordination layer of the market.

Why lower coordination costs create a governance problem

More capable models affect the market by lowering the cost of interpreting information and coordinating tasks. This allows decisions to be made more frequently, across more variables and with less direct human intervention. Organizations must formalize objectives, constraints and evidence in forms that systems can interpret.

This formalization creates both value and risk. It can make processes faster, more consistent and easier to audit. It can also privilege the signals that are most available, simplify objectives that are difficult to encode and embed proprietary assumptions into routine decisions. Once those decisions are connected to execution systems, errors or biases can be propagated across campaigns rather than remaining confined to an individual analysis.

The resulting governance problem is specific. The market does not need to make every AI model transparent to every participant. It does need sufficient visibility into material objectives, inputs, permissions, actions and performance to establish responsibility, support challenge and prevent automation from converting unresolved data or measurement weaknesses into recurring commercial decisions.

Agentic standards and interfaces become necessary when proprietary systems act across organizational boundaries. Emerging protocols, buyer and seller agent frameworks, agent registries and agentic video-buying initiatives are beginning to define how agents discover inventory, communicate with seller systems, validate decisions, manage creative, apply governance rules, activate audiences, measure outcomes and execute transactions.

From human-operated workflows to AI-orchestrated systems

Traditional advertising workflows move a client brief through planners, buyers, sellers and operations teams using a mix of judgment, platform tools, spreadsheets, email and order-management systems. AI-enabled systems can extract objectives, identify audiences, recommend inventory, generate or adapt creative, forecast reach, configure campaigns, monitor delivery, diagnose anomalies and execute approved changes through platform integrations.

“As agents become users of the system, the API becomes their equivalent of the user interface. Anything a person can do through the interface increasingly needs to be available through the API so that an agent can act efficiently.”

David Dworin, Chief Product Officer, FreeWheel

People will spend less time operating each workflow step and more time setting strategy, approving material actions, managing clients and brands, negotiating terms, reviewing legal and creative issues, governing systems and handling exceptions.

The standards dimension

Agentic advertising cannot scale through isolated platform experiments alone. If a buyer agent is expected to discover inventory, interpret publisher capabilities, evaluate audiences, understand creative requirements, compare pricing, apply governance rules, configure campaigns, monitor delivery, and reconcile measurement, it needs structured ways to communicate with other systems. If a seller agent is expected to respond to buyer requests, package inventory, enforce business rules, protect data, manage yield, and support transactions, it needs the same.

Standards must address whether independently developed agents can operate across the market in interoperable, auditable, secure and commercially trustworthy ways.

Advanced TV and video make this especially difficult. Premium video transactions are not simple commodity auctions. They may involve upfront commitments, guarantees, sponsorships, audience constraints, brand safety rules, content adjacency requirements, frequency goals, competitive separation, creative review, data restrictions, outcome measurement, and reconciliation. Agentic systems need to understand these differences and also need to express them in machine-readable form.

panels to provide representativeness, while large-scale data provides granularity. The strategic measurement task is to synthesize these sources rather than substitute one for the other (Vanheuverzwyn & Rosanvallon, 2026, pp. 18-20). In AI-enabled TV measurement, this means the signal layer should not be treated as raw data accumulation. It must be a governed process of source alignment, definition matching, modeling, validation, and disclosure.

The intelligence layer: from data to recommendations

The intelligence layer interprets signals. This is where predictive models, machine learning systems, optimization algorithms, planning models, bidding algorithms, forecasting tools, anomaly detection systems, MMMs, attribution models, and recommendation engines operate.

The intelligence layer can support forecasting reach, delivery, frequency, and outcomes; recommending audiences; identifying supply opportunities; optimizing bids; predicting creative performance; detecting delivery anomalies; interpreting measurement outputs; identifying underperforming publishers or segments; modeling incrementality; supporting MMM-based scenario planning; recommending budget reallocation; and translating results into future planning assumptions.

“Some of the best algorithms and agents will be built into the platform. But customers and partners will also have information, data and strategies that we do not. They need to be able to build their own capabilities on top.”

David Dworin, Chief Product Officer, FreeWheel

Model documentation should specify the optimization objective, data, assumptions and trade-offs. A model optimizing to lowest CPM will behave differently from one optimizing to quality-adjusted reach, incremental sales, attention-weighted exposure or long-term brand growth.

The workflow layer: rewiring how work gets done

The workflow layer is where AI changes daily operations. In this layer, AI helps users interact with complex systems. It can summarize information, answer questions, generate plans, prepare reports, create campaign objects, map data, configure workflows, and coordinate tasks across systems.

A planner may upload a brief and ask for a recommended CTV plan. A buyer may ask why a deal is underdelivering. A campaign manager may ask the system to identify which publishers are driving frequency waste. A measurement analyst may ask for a summary of reach, attribution, and incrementality findings. A creative team may request variants for different geographies or languages. A local advertiser may ask for households near specific store locations.

AI can translate user intent into operational steps, reducing dependence on specialized interface knowledge while making the resulting workflow easier to inspect.

Embedded and extensible intelligence

A further architectural distinction is emerging between intelligence that is embedded within an advertising platform and intelligence that is built on top of it. FreeWheel describes this as a “Built In, Build On” strategy. The built-in layer includes predictive models and agents developed within the platform to support forecasting, planning, pricing, bidding, pacing, performance optimization and campaign troubleshooting. The build-on layer exposes approved platform data and capabilities through APIs, software-development tools, a partner environment and a Model Context Protocol server, allowing agencies, publishers and other partners to develop their own models, agents and workflow applications.

This distinction matters because it points toward a plural rather than monolithic AI architecture. A platform provider may be best placed to develop capabilities that depend on transaction-level visibility, system-wide operational data and direct control of the execution environment. An advertiser, agency or publisher may be better placed to define the objectives, proprietary data, business rules and optimization logic specific to its own strategy. The emerging model combines platform intelligence with enterprise-specific intelligence rather than requiring one party to supply both.

FreeWheel's approach illustrates how this can extend beyond conventional software customization. Its stated objective is to allow external agents to interact directly with premium video execution infrastructure, while continuing to rely on the platform for real-time transaction processing, security, reliability and operational controls. In this architecture, the platform becomes both an application and an execution substrate: it provides its own intelligence while allowing governed third-party intelligence to operate through it.

Platforms will be judged on the AI capabilities they provide and on how safely and effectively clients and partners can build their own capabilities on top of them.

The execution layer: when AI takes action

The execution layer is where AI begins to act. This includes campaign creation, targeting changes, bid adjustments, supply selection, creative routing, audience activation, pacing changes, optimization decisions, and buyer-seller agent communication.

Execution is where AI moves from recommendation to operational authority. A system may be allowed to recommend a budget reallocation but not execute it. It may be allowed to pause a campaign under fraud conditions but not change creative. It may be allowed to adjust bids within a defined range but not accept new deal terms. It may be allowed to configure a draft campaign but require human approval before launch.

In premium video, execution rules may need to be especially careful because campaigns may involve negotiated commitments, brand-sensitive placements, category separation, audience guarantees, sponsorships, creative approvals, and contractual obligations.

The governance layer: trust, accountability, and control

The governance layer determines whether AI can be trusted. It includes data provenance, privacy controls, consent enforcement, model documentation, methodology transparency, identity assumptions, uncertainty disclosure, agent permissions, human oversight, audit logs, brand safety rules, contractual obligations, and dispute resolution.

Governance is sometimes treated as a compliance function added after innovation. That approach will not work for agentic AI. Governance must be designed into the system from the beginning.

Key governance questions include what data the AI system is allowed to use, how that data was collected, what privacy rules apply, how current the data is, what assumptions are embedded in the model, what objective the system is optimizing, what actions the agent is allowed to execute, what requires human approval, how actions are logged, how decisions can be audited, and how uncertainty is communicated.

The layers are sequentially dependent but not organizationally separate. A workflow may appear effective while relying on weak signals; an execution system may be technically secure while pursuing an unsuitable objective; and a well-documented model may still be inappropriate for the decision to which it is applied. Readiness depends on the integrity of the complete chain rather than the sophistication of any single component.

The Five-Layer Stack establishes where governance must operate. It does not, by itself, determine how much authority a particular system should receive. That question is addressed by the Delegation Model in Chapter 12, which aligns the level of human oversight and control with the risk, materiality and reversibility of the action.

Chapter 3.

Agentic Buying and the Automation of Market Workflows

Agentic buying moves AI from task support toward coordinated market action. Unlike conventional automation of bidding, pacing, reporting or trafficking, an agentic system can interpret campaign objectives, evaluate options, configure multi-step workflows, interact with external systems and take approved actions for buyers or sellers.

This changes how media decisions are prepared and executed. Premium video buying may combine direct negotiations, upfront commitments, programmatic guaranteed deals, private marketplaces, audience guarantees, creative approvals, brand-safety constraints, frequency expectations, measurement requirements and reconciliation.

Agentic systems are beginning to compress this workflow. A buyer agent may read a brief, extract objectives, identify eligible inventory, generate a recommended plan, suggest audience segments, forecast reach, create campaign structures, surface creative requirements, and prepare activation workflows for human review. A seller agent may package inventory, respond to buyer requests, enforce business rules, validate availability, preserve pricing logic, and support transaction workflows.

From planning support to actionable orchestration

The market should distinguish between three levels of AI-enabled buying. Advisory AI helps humans understand information. Workflow AI helps humans complete operational tasks. Agentic orchestration interacts with other tools or platforms to perform multi-step workflows.

Advanced TV and video are moving from advisory and workflow AI toward bounded orchestration. Agents can prepare, propose, validate and, within defined controls, execute parts of the workflow while humans retain approval for material actions.

“Before the campaign is published, the agent asks for one final review of the creative, geography, audiences and campaign setup. The agent may be able to act, but the advertiser still has an explicit approval point.”

Jonathan Moffie, Head of Agentic, Magnite

AI can now help build media plans, generate audience segments, select media partners, create customized sales packages, scenario-plan, forecast performance, and use synthetic data to support audience building, MMM, and attribution (IAB, BWG Global & Transparent Partners, 2025, p. 3). This broadening of capability is what distinguishes agentic buying from conventional automation: AI is no longer confined to a single point in the workflow but is increasingly capable of orchestrating multiple decisions across planning, activation, and measurement.

“The protections, controls and gateways have to sit on top of the infrastructure so that agents can interact safely and securely. They are beginning to spend real money.”

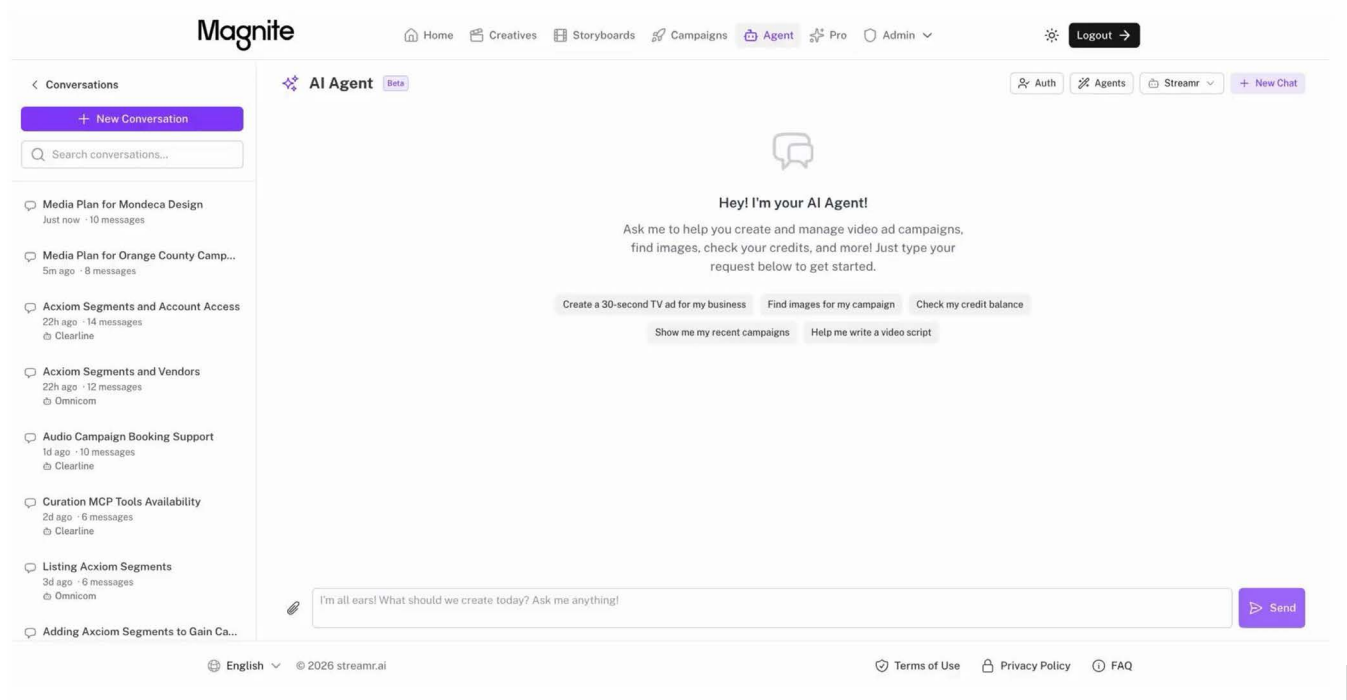
David Dworin, Chief Product Officer, FreeWheel

What workflow compression looks like in practice

In the workflow demonstrated during the Showcase, a campaign brief supplied objectives and constraints; the agent forecast reach, evaluated publisher inventory, recommended budget allocations and proposed geographic, demographic and behavioral audiences. It then prepared campaign structures across direct publisher relationships in one environment rather than handling each insertion order separately.

The same environment connected creative production to activation, allowed the advertiser to amend and approve selected campaigns, and consolidated delivery, pacing, publisher performance and audience insights.

Exhibit: From Campaign Brief to Live CTV Campaign: The Magnite Buyer Agent¹



The demonstrated workflow retained an explicit human approval point before expenditure was committed. The agent's value lay in completing preparatory, administrative and coordination work in advance of that decision, compressing exchanges among agencies, publishers and technology platforms into a guided, auditable process. The system retained an explicit human approval point before money was committed. Its value came from completing much of the preparatory, administrative and coordination work before that approval. Work that would ordinarily involve repeated exchanges among agencies, publishers and technology platforms could be compressed into a guided, auditable workflow².

Workflow compression also applies after activation. FreeWheel demonstrated a troubleshooting agent designed to investigate campaign or deal-delivery problems inside the platform where those problems are occurring. A user might ask why a campaign is underdelivering or why delivery against a deal fell sharply. The agent can inspect available operational data, identify potential causes, return a recommendation and support a continuing natural-language investigation.

Advertising-technology troubleshooting often requires reconstructing evidence across configuration, bids, inventory availability, audience rules, creative status, pacing, pricing and publisher constraints. A native agent can inspect those system events together and shorten the path from symptom to diagnosis.

¹ Magnite, CIMM AI Innovation Showcase, June 2026.

² Magnite demonstration at the CIMM AI Innovation Showcase, June 2026.

Operational agents can also make system knowledge more consistently available, reduce dependence on a small group of specialists and preserve the reasoning used to resolve recurring problems. This can turn troubleshooting into continuing campaign assurance.

The governance requirement is correspondingly clear. Diagnostic evidence, recommendations and any subsequent corrective action should remain distinguishable. An agent may be authorized to investigate and recommend without being authorized to modify pricing, targeting, inventory selection or delivery settings. The system should preserve the evidence reviewed, the conclusion reached, the action proposed and the person or rule that authorized any change.

The buyer agent and the seller agent

A buyer agent needs structured information about eligible inventory, audiences, constraints, pricing, creative requirements, measurement options and governance rules. A seller agent can supply those responses while enforcing availability, packaging, pricing logic, approval processes and publisher controls.

Standards, interoperability, and trust

Because agentic systems are entering operational use, interoperability can no longer depend solely on bespoke integrations. If every buyer agent requires a custom connection to every publisher, platform, SSP, DSP, measurement provider and data partner, advanced TV's existing fragmentation will be reproduced at machine speed.

These agent interactions could include embedded campaign-troubleshooting agents, agency operating systems connected directly to premium video execution infrastructure, outcome-oriented TV buying platforms built on established ad-serving environments, and partner portals designed to support specialized publisher applications. The agentic ecosystem is developing through multiple architectural models simultaneously rather than converging immediately around a single application or provider.

From a platform product to an agent execution environment

The emerging architecture is unlikely to consist of a single agent operating independently across the market. The Showcase pointed instead to a layered ecosystem of embedded, connected and partner-built intelligence. FreeWheel's "Built In, Build On" strategy provides a useful illustration of this model. It combines predictive algorithms and native agents developed within the platform with infrastructure intended to let customers and partners build their own applications, models and agents around FreeWheel's transaction and execution capabilities.

The built-in layer encompasses capabilities for forecasting, planning, advertiser and brand detection, bid optimization, pacing, performance optimization and audience modeling. It also includes newer agentic applications such as semantic search, planning, contextual classification and campaign troubleshooting. FreeWheel's broader published account describes dozens of optimization models already operating across areas such as invalid-traffic detection, live-event pacing, pricing, cost-per-acquisition bidding and supply-and-demand forecasting.

The build-on layer serves a different purpose. APIs, software-development tools, a Partner Portal and a Model Context Protocol server allow approved external systems to access FreeWheel capabilities and interact with the platform. This enables an agency, publisher or technology partner to apply its own data, models, objectives and business rules rather than relying exclusively on the platform's native intelligence. FreeWheel's presentation described this as a way for partners to build customized bidding agents, data augmenters, selling agents, ad-operations agents and publisher-specific applications.



Exhibit: FreeWheel's Built-In and Build-On AI Capabilities³

Exhibit: AI capabilities – FreeWheel

Predictive AI Historical data and statistical models to forecast future outcomes or behaviors	• Forecasting & Planning Models • Advertiser and Brand Detection • Bid Optimizations • Pacing Algorithms • Performance Algorithms • Audience Lookalike Modelling	• Customizable Bidding Agents • Bid & Delivery Models • Data Augmenter • Transaction Level Data
Agentic AI Autonomous models that take actions toward achieving goals, using reasoning, planning, and multi-step decision-making	• Context Engine • Troubleshooting Agent • Semantic Audience Search • Planning Agent	• Partner Portal • MCP Server • Selling Agent • Ad Ops Agents

© 2026 FreeWheel. Confidential.

The architectural significance is that agents become a new class of platform user. Human users interact through screens, menus and dashboards; agents interact through APIs, schemas and machine-readable permissions. As FreeWheel Chief Product Officer David Dworin explained during the Showcase, the API becomes the agent's equivalent of the user interface. This requires platforms to expose operational capabilities at sufficient depth for agents to perform useful work, while simultaneously adding protections, authorization controls and gateways because those agents may eventually configure campaigns, alter delivery or spend real money.⁴

Advertising platforms are being designed for two operator types: people using applications and agents invoking functions directly. Interface quality, permissions, data definitions and audit records become as important as model capability. Advertising systems are beginning to be built for two kinds of operator: people using applications and agents invoking functions directly. The quality of the underlying interfaces, permission structures, data definitions and audit records will become as important as the intelligence of the agent itself.

³ FreeWheel presentation to the CIMM AI Innovation Showcase, June 3, 2026.

⁴ FreeWheel presentation to the CIMM AI Innovation Showcase, June 3, 2026.

Exhibit: FreeWheel's "Built In, Build On" AI Architecture

Architectural component	Illustrative capabilities	Primary source of differentiation	Strategic implication
Built-in predictive intelligence	Forecasting and planning models; bidding and pacing algorithms; pricing and performance optimization; audience modeling	Platform transaction data, historical operating knowledge and direct integration with execution systems	Established machine learning remains a foundational part of the AI stack; generative and agentic systems build on rather than replace it.
Built-in agents	Planning agent; troubleshooting agent; semantic audience search; Context Engine	Native access to campaign, inventory, content and delivery data	Agents can diagnose and act within the systems where operational problems occur
Build-on algorithms and models	Custom bidding models; bid and delivery models; data augmentation; advertiser-specific outcome optimization	Client or partner data, objectives and specialist expertise	Advertisers and agencies can preserve differentiated decision logic rather than adopting a single platform objective
Build-on agents and applications	Agency operating-system integrations; selling agents; ad-operations agents; publisher-specific applications	Proprietary workflows, business rules and external enterprise systems	The platform becomes an execution substrate for a wider ecosystem of specialized agents
Connectivity and control layer	APIs; Partner Portal; MCP server; software-development tools; permissions and gateways	Interoperability, security, access control and enterprise-grade execution	Agentic scale will depend on governed access to platform capabilities, not simply on model capability

This model has important implications for interoperability. The value of an agent will depend partly on the number and quality of the systems it can access, but access cannot be unrestricted. Platforms will need mechanisms through which external applications can discover approved capabilities, invoke defined functions, respect publisher and advertiser rules, and generate complete records of the actions taken. Agentic advertising will scale through governed ecosystems of applications and connectors, not simply through increasingly capable language models.

Technical interoperability: the PMG–FreeWheel pilot

The distinction between an AI interface and genuine agent interoperability is illustrated by FreeWheel's pilot with PMG. Rather than placing a generic conversational layer over a reporting dashboard, PMG is connecting Alli, its proprietary marketing operating system, directly to FreeWheel's platform through FreeWheel's MCP-based agent infrastructure. The integration is designed to allow PMG's systems to query streaming data, monitor deal performance, identify opportunities and interact with execution workflows with limited latency.

The pilot keeps the two control domains separate. PMG retains its operating environment. FreeWheel retains its transaction infrastructure, operational data and control over permitted actions. PMG's intelligence can use FreeWheel's approved capabilities without merging the systems into one product. This illustrates an early model for agentic advertising at scale. Agencies, advertisers and publishers may each develop differentiated agents, but those agents will need governed access to transaction platforms, measurement systems, data environments and enterprise applications. The competitive advantage may reside less in owning a universal agent than in combining distinctive intelligence with reliable access to a network of execution systems.

The pilot also exposes a central governance question. "Interoperability" must not be interpreted as unrestricted system access. Useful agent integration requires explicit scopes, authenticated identities, permitted actions, data boundaries, budget limits, logging and revocation. Technical openness and operational control must develop together.

Agentic advertising requires common language for inventory discovery, audience activation, creative distribution, campaign creation, transaction validation, measurement, reconciliation, compliance, and auditability. It also requires rules for agent identity, authorization, permissioning, and action execution.

A minimum interoperability profile

An initial interoperability standard need not govern every aspect of a transaction. It should define the minimum functions required for independently operated systems to interact safely and consistently. A minimum interoperability profile should include:

1. **Authenticated agent identity:** the system and organization initiating a request must be identifiable.
2. **Scoped authority:** permissions should define which data, functions, campaigns, clients and actions the agent may access.
3. **Machine-readable transaction requirements:** inventory, audience, creative, measurement and commercial constraints should be represented in sufficiently consistent forms.
4. **Standardized status and error responses:** systems should communicate whether a request was accepted, rejected, incomplete, expired or unable to be performed.
5. **Action receipts and audit events:** material requests, recommendations, approvals and completed actions should generate reconstructable records.
6. **Revocation and reversal:** permissions should expire or be withdrawn, and reversible actions should support rollback or suspension where technically and commercially feasible.

This profile would not determine pricing, commercial strategy or optimization methodology. Its purpose would be to ensure that differentiated buyer and seller systems can identify one another, understand the authority available and preserve the records required for accountability.

In advanced TV and video, these standards must be especially sensitive to premium media workflows. A standard designed only for simple programmatic activation may not capture the full complexity of linear TV, CTV, sponsorship, direct-sold premium video, or programmatic guaranteed transactions.

The governance challenge

Agentic buying creates new governance requirements because agents can act. A recommendation is different from an action. A campaign summary is different from a campaign change. A forecast is different from a budget reallocation. A draft plan is different from an approved buy.

At a minimum, agentic buying requires governance across five dimensions: decision rights, financial controls, data permissions, auditability, and accountability. Organizations must define what agents can recommend, what they can prepare, what they can execute, and what requires human approval. Agents should operate within defined budget thresholds, pacing constraints, authorization rules, and escalation requirements. Agentic recommendations and actions should be logged.

Whose objective does the agent represent?

Agentic buying does not remove conflicts of interest; it can encode them more deeply into workflow design. A buyer-facing agent may recommend inventory, technology or measurement services supplied by affiliated companies. A platform agent may give greater visibility to inventory for which it has superior data or stronger commercial incentives. A seller agent may present availability and value through classifications that favor the seller's preferred packaging or pricing model. These outcomes need not result from deliberate misconduct. They may arise because the agent's objective, accessible data and available actions reflect the commercial position of the organization that operates it.

Organizations should disclose material affiliations and optimization objectives where an agent recommends or executes commercially consequential choices. Buyers should be able to determine whether the system considered a sufficiently broad set of eligible options, what constraints excluded alternatives and whether a recommendation creates a direct or indirect benefit for the party operating the agent. Comparable requirements should apply to measurement or attribution systems whose outputs are used to redirect expenditure.

Implications for agencies, publishers and platforms

Agencies will face substantial changes in client expectations. As manual planning, trafficking, reporting and optimization decline, the value of orchestration, governance, interpretation and accountability increases. AI will not eliminate the need for agencies, but it will change what clients need from them. The manual labor of planning, trafficking, reporting, and optimization may decline over time. The strategic value of orchestration, governance, interpretation, and accountability will increase.

Buyer agents need not commoditize all inventory. Premium video can retain or increase value when relevant attributes are represented accurately in machine-readable form. Premium video may become more valuable if agents can understand its value accurately. But that value must be expressed in machine-readable form.

The practical test of agentic buying is whether buyer and seller systems can interact under clear commercial rules, bounded authority and reconstructable decision records.

Chapter 4.

Creative-to-Activation: Lowering the Cost of Entry to CTV

Television advertising has long required video production, specialized campaign setup and coordination among agencies, platforms and publishers. CTV reduced some distribution barriers, but advertisers still need to adapt assets, choose buying routes, configure campaigns and interpret results. AI can connect creative production, planning and activation so that an advertiser can move from a business objective to an approved asset, plan and campaign setup more quickly. The maturity and reliability of these workflows vary.

Generative creative production

Generative AI can reduce one of the most obvious barriers: the production of usable video assets. AI-enabled creative systems can generate scripts, select or create visuals, produce storyboards, adapt brand assets, generate voiceover, add calls to action, translate copy, create multiple versions, and adapt ads to different platform formats.

“We built Streamr to democratize CTV by making it possible for advertisers to generate a television commercial in seconds and launch it themselves. The goal is to make CTV simple, affordable and effective for the millions of brands already advertising in search and social.”

Jonathan Moffie, Head of Agentic, Magnite

For small businesses, this may provide a first practical route into video advertising. A business with a website, logo, product images and an offer can produce a usable asset without commissioning a full traditional production process. For agencies and larger advertisers, the principal uses are prototyping, variant generation, localization, testing and iterative adaptation.

A creative workflow can begin with a business name, website or product. The system identifies relevant brand information and imagery, generates or adapts assets, produces scripts and storyboards, adds music or voiceover and allows the advertiser to revise the output. It can also translate copy and produce variants for connected-TV home screens, pause formats and other publisher requirements.

Generative AI can produce families of assets for different audiences, languages, publishers, interfaces and campaign objectives. When connected to planning and activation, creative production becomes part of campaign design, testing and optimization rather than a separate preliminary stage. It makes it possible to develop a family of assets suited to different audiences, languages, publishers, interfaces and campaign objectives. When connected directly to planning and activation, creative production becomes part of a continuous system of campaign design, testing and optimization rather than a separate preliminary stage⁵.

Generative AI lowers production barriers but does not replace creative strategy, brand stewardship, claims review, legal oversight or quality control. It lowers production barriers, but it does not eliminate the need for brand stewardship, claims review, legal oversight, creative judgment, and quality control.

5 Magnite presentation and demonstration at the CIMA AI Innovation Showcase, June 3, 2026.

Generative creative raises provenance, rights, trust and brand-integrity issues. Synthetic-media detection, content provenance, copyright, dataset bias, hallucination, power dynamics and transparency labeling remain relevant research and practice priorities (AI4Media Consortium, 2024, pp. 44–61). Video-advertising workflows should preserve review, rights management, disclosure and claims substantiation.

From brief to plan to activation

AI-enabled planning tools can read a brief, identify the campaign objective, extract audience and geography requirements, recommend channels or publishers, estimate reach, suggest budget allocation, and identify relevant targeting parameters. These systems can reduce the time required to move from a marketing objective to a structured plan.

Operational change occurs when AI planning connects directly to campaign activation. An AI system can generate campaign structures, create publisher-level configurations, populate fields, prepare deal setup, route creative, apply targeting, and present the campaign for human approval. The human still reviews and approves, but the manual assembly work is substantially reduced.

AI can lower two fixed costs that have historically limited participation in premium video: producing acceptable television creative and employing specialist labor to configure campaigns and coordinate publisher relationships. AI can lower two fixed costs that have historically limited participation in premium video: the cost of producing acceptable television creative and the specialist labor required to configure campaigns and coordinate publisher relationships. As those costs fall, CTV may become commercially viable for advertisers whose potential media investment was previously too small to justify the expense and complexity of entry.

The effect should not be overstated. Media minimums, creative review, claims substantiation, measurement, platform learning periods and the advertiser's own capacity to manage a campaign remain material. The relevant economic test is whether AI reduces the total cost of participation, not simply the time required to generate an asset or populate campaign fields.

“We can create nine direct insertion orders with different CTV publishers in a matter of minutes. That process would normally take weeks of emails and coordination, but the negotiation and campaign creation can now happen in the same environment.”

Jonathan Moffie, Head of Agentic, Magnite

Expanding TV's advertiser base

Lower costs and simpler workflows may make CTV viable for advertiser groups historically underrepresented in premium video, including local service businesses, regional retailers, franchise systems, restaurants, healthcare providers, auto dealerships and search or social advertisers testing video.

For publishers, this may create incremental demand for unsold or underused inventory and make local or regional campaigns easier to service. Unsold or underutilized inventory can be matched with new advertisers. Local and regional campaigns can be scaled more efficiently. Creative barriers that once limited demand can be reduced.

The potential demand pool is materially larger than the traditional television advertiser base – historically, a relatively small number of advertisers have been responsible for a large proportion of television spending, versus the more than nine million brands already advertising through search and social media. For many of these businesses, the constraint is not an absence of interest in video. It is the combined cost and complexity of producing an acceptable asset, adapting it to platform requirements and navigating the buying process.



The commercial opportunity extends beyond making production less expensive for established television advertisers. It involves creating a practical route into premium video for businesses that have become accustomed to self-service creative, rapid campaign setup and measurable performance in digital channels. For publishers, this could broaden the advertiser base while creating additional demand for inventory that is difficult to monetize through conventional national television sales processes⁶.

Quality control and measurement requirements

Creative-to-activation workflows require controls at two distinct stages. First, the creative should be reviewed for factual accuracy, brand consistency, rights clearance, legal compliance, platform suitability and any required disclosure of synthetic content. Second, the workflow should preserve a record of source assets, material prompts and alterations, approvals and usage rights.

Technical acceptance should remain distinct from substantive approval. An asset may satisfy file, format and delivery requirements while still containing an inaccurate claim, unauthorized material or content inconsistent with advertiser or publisher standards. Advertisers remain responsible for claims and brand approval; platforms and publishers remain responsible for acceptance policies; and technology providers should make provenance and review history available to authorized parties.

Adoption also depends on evidence of effectiveness. Small and mid-sized advertisers need clear information about delivery, reach and contribution to business outcomes. Connecting creative, activation, measurement and optimization agents can shorten the cycle from campaign launch to evaluated adjustment.

Generative production may expand access while also increasing low-quality or repetitive creative. Success should be judged by whether the resulting advertising is distinctive, accurate, effective and suitable for the placement – not by asset volume or production speed.

⁶ Magnite presentation to the CIMM AI Innovation Showcase, June 3, 2026.

Chapter 5.

AI, Identity, and Real-World Audiences

AI is often associated with synthetic content, virtual assistants and digital automation. The Showcase also illustrated how AI can connect advertising systems to physical locations and household behavior.

“AI has been heavily focused on the synthetic digital world. The opportunity is to bring the digital and physical worlds together by connecting AI-driven audiences to real households in real geographies.”

Jason Manningham, CEO and Founder, Blockgraph

Much consumer behavior remains local and geography-dependent. People visit stores, restaurants, clinics, dealerships, bank branches, airports, entertainment venues and service locations. Proximity to those locations can influence what consumers buy, where they go and which services they consider.

Traditional TV geography has often been too broad to operationalize this fully. DMAs, ZIP codes, regions, and local market definitions are useful but imprecise. They do not always reflect the practical trade areas around specific stores, service locations, retail distribution footprints, or category-specific travel behavior. AI can help close this gap by turning real-world locations into household-level audiences that can be activated across TV and streaming environments.

Why proximity matters

For a QSR advertiser, households within a short radius of a restaurant are more likely to visit than households across the DMA. For a healthcare provider, households near a clinic or facility may be more relevant than broad regional audiences. For an airline, households within practical driving distance of served airports may be more valuable than general travel intenders. For a CPG brand, households near stores where the product is actually available may be more relevant than households in markets where distribution is weak.

“The closest household to a store is often its most valuable household. The concept is not new. What is new is the ability to act on it at scale.”

Jason Manningham, CEO and Founder, Blockgraph

The continuing importance of physical geography helps explain this opportunity. Materials presented during the Showcase estimated that 85% of commerce still occurs in the physical world and that 80% of store purchases are made within 15 minutes of the purchaser's home. These figures should be treated as directional market evidence rather than independent CIMA estimates, but they illustrate the central point: national and regional media plans often operate at a much broader geographic level than the commercial footprint within which a consumer is likely to act⁷.

7 Blockgraph presentation to the CIMA AI Innovation Showcase, June 2026.

Exhibit: AI-Powered Proximity Targeting and Instant Audience Creation⁸

Proximity Targeting Powered by Instant Audiences

Selected Signal: Proximity

Required Information
Enter the business details and search for locations to include in your audience

* Segment Name
Hts within 3 Mi of Whole Foods 30 / 100

* Business Name or URL
Whole Foods 11 / 100

States
All States (default)

Do you want to select specific cities within the states you've selected?
☒ No ☐ Yes

* Radius (miles)
3 Min. 1 Max. 50

Search Edit

Locations Found 532

Estimated Households 26,806,680

Previous Next



From location data to household audiences

The demonstrated workflow converted location intelligence into activation-ready household audiences. A user could enter a business, website, store list, retail footprint, airport list, facility network or custom location set; validate locations; apply a radius of one to 50 miles; estimate household reach; and generate an audience segment. The method could be applied to a single site, a regional network or thousands of outlets, with trade-area definitions adjusted by category and use case⁹.

The radius can vary by category. A three-mile radius may make sense for a QSR in an urban market. A broader radius may be appropriate for an airport, hospital system, auto dealership, furniture retailer, or regional attraction. Different categories have different catchment areas, and AI can help operationalize those differences.

The most immediate use cases are in categories where physical presence matters: restaurants, retail, consumer goods, healthcare, financial services, auto, home services, travel, and transportation. The immediate use cases are categories in which physical presence shapes demand, including restaurants, retail, healthcare, financial services, automotive, home services, travel and transportation.

⁸ Blockgraph, CIMM AI Innovation Showcase, June 2026.

⁹ Blockgraph demonstration at the CIMM AI Innovation Showcase, June 3, 2026.

Identity as the anchor

Proximity targeting requires an identity foundation that connects locations to households, activation endpoints, exposures and outcomes. Without that framework, location data remains descriptive rather than operational.

AI does not correct weaknesses in that identity foundation. It increases their operational significance because identity linkages can become direct inputs to audience construction, activation, measurement and optimization. An incomplete, stale or incorrectly inferred household connection may cause the wrong households to enter or leave an audience, distort the estimated reach of a location-based campaign, misattribute an exposure or outcome, and ultimately influence where subsequent investment is directed. As audience creation becomes faster and more scalable, the same linkage error can be propagated across thousands of locations or campaign configurations rather than remaining confined to a single retrospective analysis.

The appropriate standard is not that every linkage must be deterministic or certain. Different use cases can tolerate different levels of uncertainty. The requirement is that the entity being represented, the method and confidence of the linkage, its freshness, its permitted uses and its known limitations are sufficiently visible to determine whether it is fit for the proposed targeting or measurement task.

CIMM's Identity Infrastructure 2.0 report identifies deterministic anchoring where feasible, explainable linkage, documented provenance, privacy-by-design controls, interoperability and measurement-grade validation as foundations of durable identity infrastructure (CIMM, 2026, p. 7). AI-enabled proximity depends on an identity spine that is current, transparent and fit for automated audience and measurement decisions.

Fairness, sensitive uses and geographic proxies

Proximity is not a neutral signal in every application. Residential geography can correlate with income, ethnicity, health status and other characteristics that may create legal, ethical or reputational risk, particularly in healthcare, financial services, housing, employment and other sensitive categories. An audience does not become appropriate merely because it can be constructed accurately.

Governance should address the purpose of the campaign, the sensitivity of the locations involved, minimum audience sizes, exclusion rules, permitted radius definitions and the possibility that geographic optimization produces indirect discriminatory effects even where protected characteristics are not explicitly used. Sensitive locations and categories may require additional review, aggregation or prohibition.

These controls should apply both to the initial audience definition and to subsequent optimization. An algorithm that repeatedly reallocates investment toward geographies producing the most observable response may reinforce historical patterns of access or exclusion. Organizations should evaluate distributional effects alongside efficiency and campaign performance.

From audience creation to outcome accountability

Outcome accountability requires a consistent identity foundation linking activation to exposure and business results. Relevant measures may include store visitation, sales, appointments, bookings or performance relative to broad-market delivery. AI can analyze these patterns and return them to planning, but causal evaluation remains necessary.

These questions require causal evaluation rather than simple comparison of targeted and untargeted households. Households close to a location may already be more likely to visit or purchase, independent of advertising exposure. Credible assessment may require geographic holdouts, matched-market designs, store-level experiments, pre-specified comparison groups or other methods capable of distinguishing the effect of advertising from the pre-existing effect of proximity.

The appropriate success criterion is incremental change relative to a credible counterfactual, not merely a correlation between closeness, exposure and response.

“Household identity is the anchor. Proximity puts it to work by connecting the reach of television to the geography of real-world performance.”

Jason Manningham, CEO and Founder, Blockgraph

AI-supported proximity can connect television delivery to local commerce only when household identity is reliable and outcome measurement can distinguish incremental response from pre-existing geographic propensity.

Chapter 6.

AI-Powered Measurement and the Shift from Reporting to Optimization

AI changes the practical role of measurement by reducing the time and labor required to prepare data, reconcile definitions, identify anomalies and interpret results. When those activities can occur while a campaign remains active, measurement can influence pacing, allocation, creative, audience and supply decisions before the investment is complete.

Faster measurement can affect decisions while a campaign is running. That makes methodological errors more consequential. A weak signal connected to an allocation system can influence repeated actions across campaigns.

Not all measurement should operate at the same cadence or support the same degree of delegated action. Delivery diagnostics may be sufficiently timely and reversible to guide in-flight correction. Attribution or modeled outcome signals may support optimization when their assumptions and uncertainty are understood. Incrementality, brand effects and strategic allocation evidence frequently require longer observation periods, experimentation or model comparison. Measurement cadence and delegated authority should match the fitness of the evidence supporting the decision.

Measurement outputs connected to operational systems should carry information about the kind of evidence they represent and the decisions they are qualified to support. At a minimum, the receiving system should be able to determine:

- Whether the result is descriptive, observational, experimental or modeled.
- The population, campaign and time period to which it applies.
- When the underlying data was last refreshed.
- The material assumptions and known coverage gaps.
- The uncertainty associated with the estimate.
- Whether the output is suitable for diagnosis, planning, optimization, reconciliation or contractual accountability.
- Whether a holdout, experiment, human approval or other additional control is required before action.

A technically machine-readable output should not acquire greater decision authority than its method supports.

The measurement problems that AI is trying to solve

Advanced-TV measurement faces fragmentation and rising expectations for speed. Advertisers buy across linear TV, CTV, streaming, FAST, digital video, social platforms, retail media, search, audio, out-of-home and owned channels, each with different data, identifiers, reporting practices and methods. At the same time, advertisers expect measurement to inform in-flight optimization, budget allocation, creative changes, audience refinement and future planning.

Traditional measurement systems often struggle with this combination for three connected reasons. First, the data required for cross-media analysis remains distributed across platforms, clouds, publishers and retail-media environments, creating cost, latency and governance complexity whenever it must be transferred, matched and reconciled. Second, reporting remains siloed: gaps in publisher or platform coverage can leave important parts of the customer journey unobserved, distort reach and frequency estimates and cause conversions to be attributed disproportionately to the channels that are easiest to measure. Third, measurement often stops at the production of an output rather than being connected to a subsequent decision. Teams may still spend weeks mapping taxonomies, validating files, interpreting large reports and converting findings into recommendations, by which time the campaign

may already have concluded. These problems compound one another. Fragmented inputs produce incomplete reporting, and incomplete reporting limits the quality of any optimization that follows.

“To do this well, AI needs high-quality signals, connected identity and an interoperable environment in which insights can actually translate into action.”

Jack Foster, Head of Cross Media Intelligence, LiveRamp

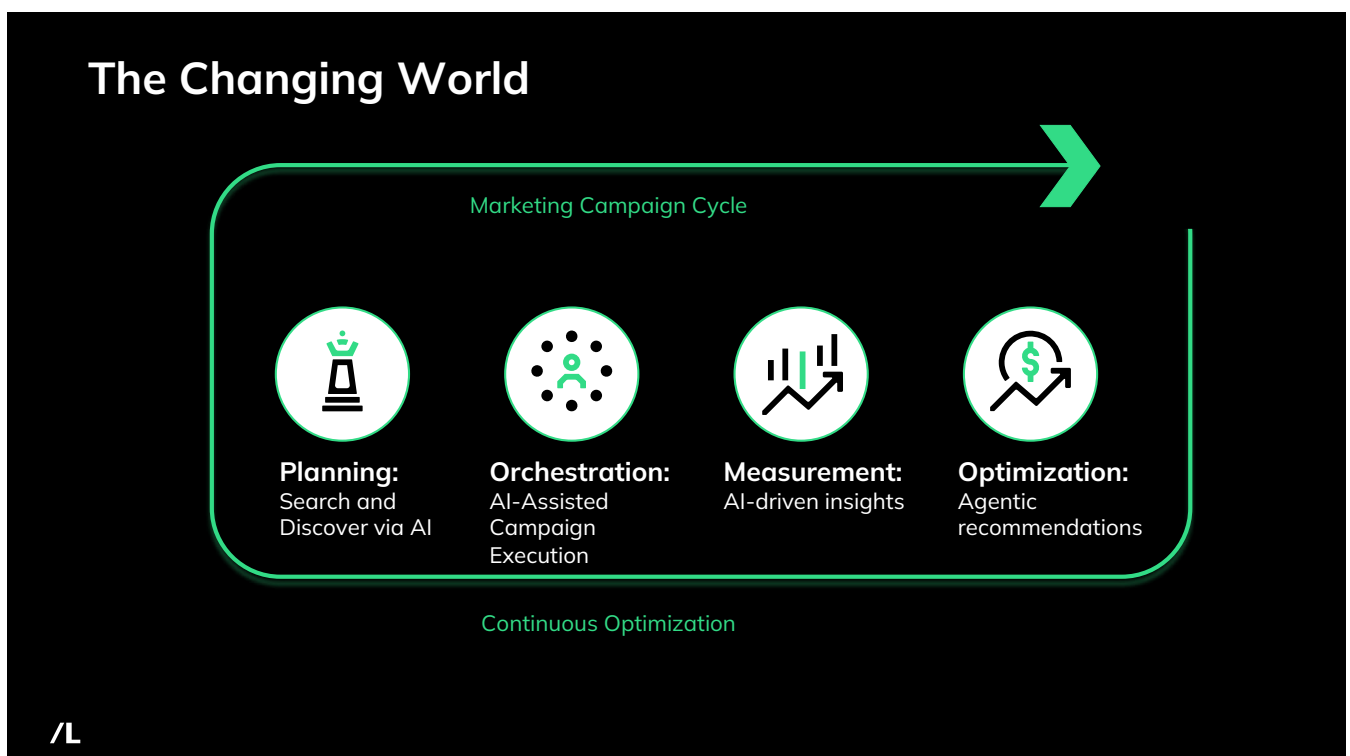
Survey evidence shows broad but incomplete adoption of advanced measurement. Most U.S. buy-side decision-makers use at least one advanced measurement approach: 76% use incrementality tests, 73% use attribution analysis, and 67% use MMM, but only 39% use all three together (IAB & BWG Global, 2026, p. 6). This highlights a central problem: sophisticated measurement methods are widely present, but they are not always consistently integrated into coherent decision systems.

Between 60% and 75% of marketers say current advanced measurement approaches do not perform very well on important dimensions including rigor, channel coverage, timeliness, transparency, trust, and operational efficiency (IAB & BWG Global, 2026, p. 7). These findings indicate continuing gaps in measurement integration, timeliness, interpretability and usability.

From reports to decision support

Traditional measurement separated campaign execution from later analysis. AI-enabled systems can ingest data more frequently, map inputs, detect anomalies, interpret performance and return recommendations to planning or activation. Measurement thereby becomes an input to publisher, creative, audience, geography, frequency and budget decisions.

Exhibit: The AI-Enabled Marketing Campaign Cycle¹⁰



¹⁰ LiveRamp, CIMM AI Innovation Showcase, June 2026.

Actionability should not be equated with immediacy. Some signals are appropriate for real-time or in-flight adjustment; others become reliable only after sufficient observations, experimental analysis or longer outcome windows. A slower measure can still be highly actionable if it changes future planning, budget allocation or creative strategy. AI-enabled measurement systems should preserve the time horizon and uncertainty appropriate to each method rather than forcing every measure into a continuous optimization loop.

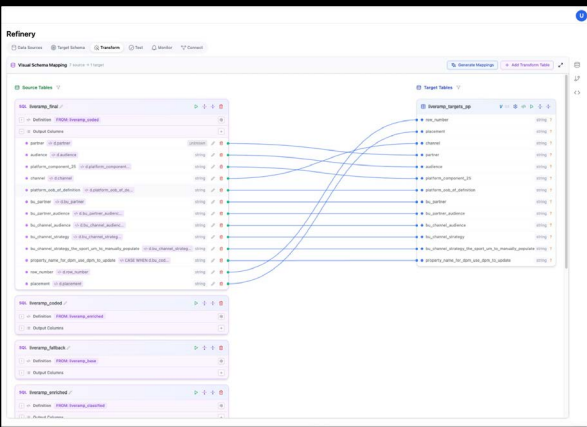
AI agents in measurement workflows

Several distinct agentic measurement functions are now emerging. A mapping agent can ingest ad-server reporting and publisher-level log data, learn a customer's reporting hierarchy and taxonomy, classify fields and identify inconsistent naming conventions. One pilot described during the Showcase was designed to reduce the mapping burden for the brand and measurement provider by more than 50%, addressing a significant source of latency before analysis can begin.

Exhibit: The Mapping Agent: Automating Data Ingestion and Taxonomy Alignment¹¹

Mapping Agent





In pilot with Datalinx AI to:

- **Ingest Raw Data:**
Take raw inputs from ad server reports and pixel/direct log publisher connections.
- **Model Training:**
Train customer-specific model on reporting hierarchy and taxonomy.
- **Efficiency Gains:**
Reduce mapping burden on brand and LiveRamp side by >50%, speeding time to value.

“The industry has spent a long time confusing outputs with answers. A chart alone does not improve performance. A recommendation connected to the right signals and surfaced at the right time can.”

Jack Foster, Head of Cross Media Intelligence, LiveRamp

¹¹ LiveRamp, CIMM AI Innovation Showcase, June 2026.

A refresh agent can then inspect exposure, conversion and audience inputs, identify new or unmapped identifiers, update reporting parameters, orchestrate processing jobs and assist with troubleshooting. A results agent can interpret cross-media outputs and turn them into recommendations concerning publishers, audiences, creative, social, programmatic and CTV investment.

Exhibit: The Refresh Agent: Continuous Quality Assurance and Workflow Orchestration¹²

Refresh Agent

Embedded orchestration agent that:

- Pulls in QA data across all input sources (exposures, conversions, audiences)
- Allows for on the fly updates to reporting parameters
- Checks for new IDs that need to be mapped and grouped
- Orchestrates jobs & aids with troubleshooting

The screenshot displays the 'HillsPets_R+F_L+A' interface. On the left is a sidebar with navigation links: JiveRamp, Site Reports, Search, JiveRamp AI, Dashboard, Data In, Marketplace, Data Management, Data Out, Insights, and JiveRamp Intelligence. The main content area shows 'Exposure Dimensions' with two tables: 'Placement ID' and 'Creative ID'. Both tables list metrics like Name, Status, % Mapped, and Last Edited. The right-hand panel, titled 'XMI Agent', contains configuration options for 'Basic Setting', 'Modelling Configurations', 'Filter by Dimensions', 'Select Audience Segments', and 'Select Conversions'. It also includes a 'Reply...' section with buttons for 'New Chat' and 'Recent Chats'.

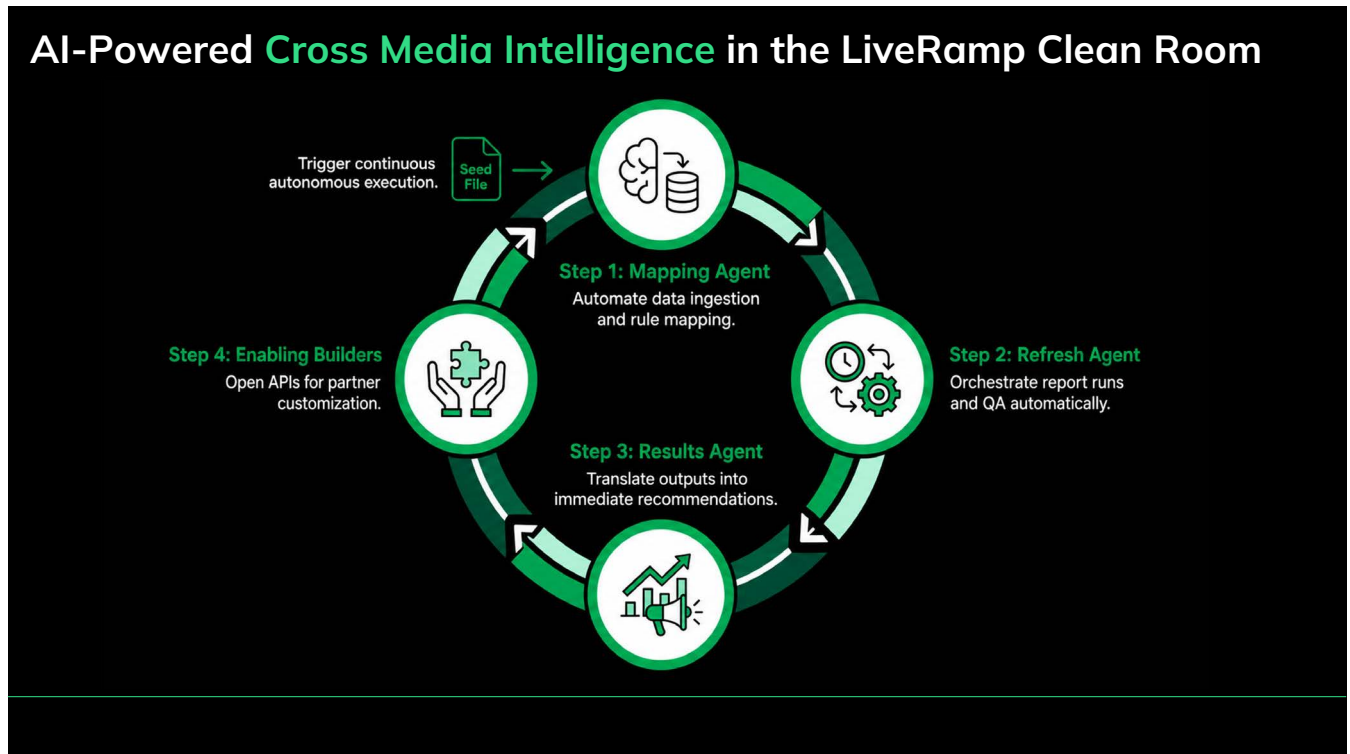
/L

Together, the mapping, refresh and results agents form one measurement workflow: prepare evidence, maintain the analytical environment and convert findings into a proposed action. The first prepares the evidence, the second maintains the analytical environment, and the third converts findings into a proposed next action¹³.

¹² LiveRamp, CIMM AI Innovation Showcase, June 2026.

¹³ LiveRamp, CIMM AI Innovation Showcase, June 2026.

Exhibit: AI-Powered Cross-Media Intelligence in the Clean Room¹⁴



At this scale, the limiting factor is the ability to identify material findings, connect them to the advertiser's objective and determine the appropriate action – not the production of additional data. It also reported that a single reporting period may generate between half a million and one million rows of metrics. At this scale, the principal constraint is not necessarily the production of more data, but the capacity to determine which findings are material, how they relate to the advertiser's objective and what action should follow.

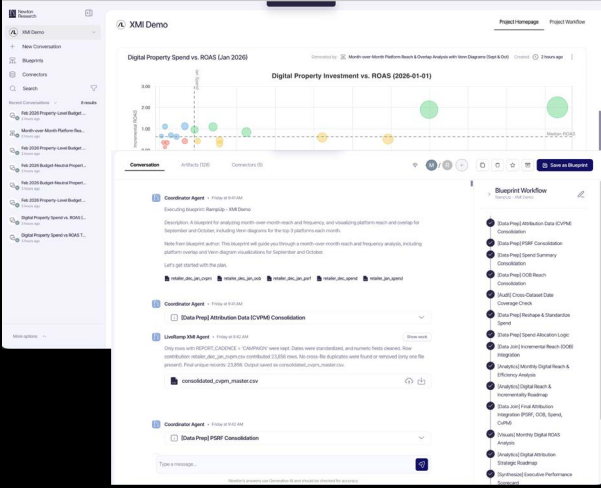
This is where agentic interpretation may create value beyond conventional reporting automation. LiveRamp¹⁵ indicated that human teams can require two to three weeks to interpret some cross-media measurement outputs and translate them into recommendations, whereas its pilot Results Agent is intended to produce publisher, audience, creative and channel recommendations within seconds. These figures are company-reported and should not be treated as general performance benchmarks. They nevertheless illustrate the economic proposition: AI can reduce the interval between analytical production and operational response, increasing the likelihood that measurement influences decisions while those decisions remain reversible.

¹⁴ LiveRamp, CIMM AI Innovation Showcase, June 2026.

¹⁵ LiveRamp presentation and demonstration at the CIMM AI Innovation Showcase, June 3, 2026. Operational figures and performance claims are company-reported and have not been independently audited by CIMM.

Exhibit: The Results Agent: Turning Cross-Media Measurement into Optimization Recommendations

Results Agent



In pilot with Newton to:

Instant Optimization:
Take outputs of XMI reporting and create instantaneous media optimization recommendations.

Multi-Channel Metrics:
Includes metrics like publisher, creative, audience optimization across social, programmatic, CTV, etc.

Future Forward:
Early pilot for Agentic Buying.



This architecture also changes the location of measurement in the campaign cycle. Rather than exporting results into a separate dashboard or presentation, an agentic system can return recommendations to the planning or activation environment from which the investment originated. Measurement becomes part of an operational feedback loop: data is connected, mapped and checked; delivery and outcomes are evaluated; findings are interpreted; and the resulting evidence is passed back into the systems responsible for allocation and execution.

The architecture is also becoming extensible. LiveRamp distinguishes among agents embedded in its own platform, agents developed with specialist partners and agents built by clients or partners within its governed environment. This model recognizes that different parties possess different forms of intelligence. A measurement platform may provide identity, data connectivity, recurring workflow orchestration and methodological templates; a specialist partner may contribute a particular analytical capability; and an advertiser or agency may contribute proprietary objectives, taxonomies, data and decision rules. The resulting system is not a single universal measurement agent, but a governed environment in which multiple agents can operate against shared data and workflow controls.

As this feedback loop becomes more continuous, AI may also materially change measurement cadence. Buy-side decision-makers expect AI to help increase the frequency of incrementality testing from approximately three to five tests per year to more than eleven, while shifting attribution and MMM from annual or biannual exercises toward monthly runs (IAB & BWG Global, 2026, p. 13).

Cross-media intelligence and connected identity

AI-powered measurement depends on connected data. To measure reach, frequency, incrementality, lift, attribution, and outcomes across fragmented channels, systems need ways to connect exposures, audiences, conversions, and business results. That requires identity, clean rooms, data collaboration, and interoperable data structures.

Cross-platform reach and frequency depend on connected identity. Attribution needs exposure data, and outcome optimization needs outcome data. Sensitive data collaboration also requires governed environments and common taxonomies. AI can help with mapping and interpretation, but it cannot create trustworthy measurement from fundamentally disconnected or unreliable inputs.

Connectivity should not be confused with unrestricted access. Some direct publisher integrations remain subject to brand-specific review and approval, reflecting contractual rights, privacy requirements, data-use restrictions and publisher governance.

Agentic measurement will need to operate through scoped permissions that specify which advertiser, dataset, purpose and analytical output are authorized. Technical interoperability can make approved collaboration faster, but it should not bypass the institutional controls governing whether that collaboration is permitted.

The risk of automated misinterpretation

The shift from reporting to optimization increases the consequences of measurement error. If a report is wrong, a human may misread it. If a signal feeding an AI system is wrong, the system may scale the error across campaigns, budgets, audiences, and future models.

Brand-specific review and approval for some publisher integrations reflect contractual rights, privacy rules, data-use restrictions and publisher governance. This risk is especially important in advanced TV and video because measurement remains complex. Different environments may expose different identifiers. Different platforms may use different methodologies. Some channels may produce richer data than others. Some outcomes may be easier to observe. Some premium video value may be underrepresented in short-term conversion data. AI-powered measurement systems should disclose uncertainty and distinguish between observed data, modeled estimates, inferred relationships, and recommended actions.

“AI is helping teams move faster from insight to action. It allows measurement to become a driver of better decisions rather than simply a record of what happened in the past.”

Jack Foster, Head of Cross Media Intelligence, LiveRamp

Managing feedback and self-reinforcement

Operational measurement can also create feedback effects. When an allocation system acts on a metric, it changes the pattern of exposure and the data on which subsequent estimates are based. Repeated optimization may concentrate expenditure in environments already favored by the model, reduce exploration and make alternative explanations harder to test.

This creates a risk of self-reinforcing allocation. A channel may receive more investment because it produces the most observable response, then generate still more observable data because it received more investment. Conversely, channels associated with slower, less granular or less directly attributable effects may receive insufficient expenditure to generate new evidence.

AI-enabled decision systems should preserve holdouts, experimentation, model comparison and explicit exploration rules. Material allocation decisions should distinguish between evidence generated through observational optimization and evidence supported by causal testing. Operational speed should not remove the conditions required for causal learning.

Chapter 7.

MMM, Outcomes, and AI-Driven Decision Systems

Marketing mix modeling is gaining renewed strategic importance as privacy constraints, signal loss, media fragmentation and demand for business-outcome evidence weaken channel-by-channel measurement. Advertisers also need planning tools that account for pricing, promotion, distribution, competition, geography, seasonality, macroeconomic conditions and other non-media drivers.

MMM evaluates the relationship between aggregate marketing activity and business outcomes while accounting for those factors. Its outputs can support scenario planning and budget allocation, making MMM a relevant source of outcome-oriented evidence for AI systems.

AI does not fundamentally change the econometric principles underpinning MMM. Instead, it changes the economics of applying MMM. By automating data preparation, scenario generation, model interrogation and interpretation, AI reduces the cost of incorporating MMM into routine planning decisions. As these costs fall, MMM becomes practical for more organizations and increasingly capable of informing continuous budget allocation rather than periodic strategic reviews.

The underrepresentation of emerging media channels reinforces the strategic importance of MMM modernization. CTV, retail media, creator-led formats, gaming, and commerce media remain underrepresented in some advanced measurement systems, potentially distorting ROI estimates and contributing to misallocated spend (IAB & BWG Global, 2026, p. 27). If AI planning systems inherit underrepresentation from existing MMM inputs, they may systematically underweight emerging and premium video environments.

Greater interest in MMM should not be confused with uniform adoption or methodological convergence. Models differ in data requirements, specification, priors, treatment of non-media factors, geographic granularity and validation. Many advertisers also lack the data, specialist capacity or organizational processes required to integrate model outputs into routine planning. The near-term transition is likely to be uneven: some organizations will use continuously refreshed models within planning systems, while others will continue to commission periodic studies whose recommendations require substantial interpretation.

From retrospective analysis to forward-looking planning

Historically, MMM was often used to explain the past. Analysts gathered historical data, built models, estimated contribution, and presented findings. The process could be expensive, slow, and disconnected from day-to-day planning.

Modern MMM is becoming faster, more accessible, and more integrated into workflow. Open-source tools, automated pipelines, cloud infrastructure, and AI-enabled interfaces are making MMM easier to operate and interpret. More importantly, MMM is increasingly being used for forward-looking planning rather than purely retrospective analysis.

Forward-looking MMM evaluates how changes in budget, channel mix, premium video investment, geography, competitive activity or promotion could affect outcomes.

When MMM becomes an input to allocation

As MMM becomes embedded in planning and decision systems, its outputs may influence a larger number of allocation choices and be refreshed more frequently. This changes the model's operational role. A result that previously informed periodic strategic discussion may become a continuing input to scenario generation or budget recommendation.

The authority assigned to that input should remain consistent with the model's design. A model calibrated to explain quarterly or annual channel-level variation should not automatically govern daily bidding, publisher selection or other decisions at a level of granularity it was not built to identify. More frequent use increases the need to specify what the model may inform, not to assume that a faster model supports every faster decision.

Analysts may question anomalies or compensate for missing information. An automated allocation system can act on a weak signal repeatedly. Measurement limitations therefore become operational risks when a model is connected to execution.

As a result, the quality of model inputs becomes highly consequential: media spend and exposure data, channel definitions, impression and GRP definitions, reach and frequency inputs, geography and timing, pricing and promotion variables, distribution and availability, competitive activity, seasonality, macroeconomic factors, attention and quality signals, creative variables, prior evidence from experiments, incrementality studies, and business outcome data.

The risk for premium video

Premium video faces a specific risk in AI-driven MMM environments. Some media channels produce fast, granular, easy-to-ingest data. They may have strong platform integration, frequent reporting, and clear short-term conversion signals. Other channels, including premium video, may produce effects that are broader, longer-term, harder to isolate, or less visible in direct response data.

If AI systems and MMM workflows reward immediacy, granularity, and ease of ingestion, premium video can be underrepresented. The issue lies in the surrounding data and evidence environment rather than MMM as a method.

Input governance becomes more consequential as AI moves from data preparation toward interpretation and decision-making. AI is currently used primarily for data-intensive tasks such as cleaning, labeling, normalizing, and collecting media-performance data. Users expect it to move into more strategic activities over the next one to two years, including attribution outcome matching, incrementality-test design and analysis, and MMM tuning (IAB & BWG Global, 2026, p. 10). As AI activity moves from preparation toward interpretation and decision-making, the quality of model inputs and priors becomes more consequential.

Media quality, experimentation and priors

Validated media-quality and attention evidence may help address the underrepresentation of exposure conditions in MMM, particularly where conventional inputs capture delivery volume more effectively than the advertising experience. Their inclusion should depend on construct validity, incremental explanatory value and the avoidance of double counting with correlated media variables. A quality or attention measure should not be added merely because it is available or machine-readable.

MMM becomes stronger when supported by experimentation. Geo-tests, lift studies, incrementality experiments, and other validation methods can create evidence that informs model priors. This is particularly important for premium video. The market needs evidence libraries that document premium video's effects across categories, objectives, time horizons, audiences, and contexts.

An emerging measurement architecture brings marketing mix modeling, attribution and controlled experimentation into a connected evidence system without treating them as interchangeable. Experiments can provide causal evidence against which modeled relationships are tested or calibrated; MMM can place those findings within a broader account of media and other business drivers; and attribution can provide more granular evidence about observable exposure-to-outcome pathways. The value lies in combining these methods while preserving the distinct evidentiary status of each.

Kochava's AIM provides one current example of this approach. The platform combines MMM with self-service incrementality testing whose experimental results can be used to validate and calibrate model estimates and inform strategic budget decisions. The broader principle is more important than the individual implementation: faster and more integrated measurement should increase the use of causal validation, not blur the distinction between modeled association and experimentally supported incrementality. Granular identity or outcome linkage can improve observability, but greater identifier-level precision does not by itself establish causality.

For MMM, machine-readable quality signals matter only when they capture constructs relevant to model specification and advertiser objectives. Historically, qualities such as trusted editorial environments, co-viewing, contextual suitability and attention were primarily communicated through sales narratives and human judgement. AI requires these characteristics to be represented as structured, machine-readable signals before they can systematically influence automated planning and optimization.

Making a construct machine-readable does not settle how it should be measured, compared or valued. Attention, context, prominence, suitability and exposure quality are distinct concepts. A structured signal should identify the construct represented, the method used, the population and environment to which the estimate applies, its uncertainty and the decision for which it is considered fit. Machine-readability should increase methodological visibility, not convert contested constructs into apparently universal facts.

Potential uses and limitations of synthetic data are considered separately in Appendix C.

Exhibit: From Retrospective Measurement to Operational Decisioning¹⁶

Stage	Primary output	Typical cadence	Relationship to action	Principal assurance requirement
Reporting	Description of past delivery or performance	Periodic or post-campaign	Human interpretation after activity	Accuracy and methodological clarity
Decision support	Diagnosis, comparison and scenario analysis	Regular or on demand	Informs human planning and optimization	Comparable inputs and appropriate uncertainty
Operational measurement	Structured signals integrated into active workflows	Near-real-time or in-flight	Influences campaign decisions while activity continues	Timeliness, interoperability and fitness for use
Agentic measurement	Systems ingest, interpret and act on evidence within defined authority	Continuous or event-driven	Supports or executes bounded actions	Permissions, auditability, validation and accountability

¹⁶ Cimm synthesis. The stages describe increasing operational integration, not an assumption that every measurement function should become autonomous.

Governance when MMM influences allocation

Governance should not seek to eliminate legitimate methodological variation. It should make that variation visible and define the decisions for which each model is fit. Where MMM recommendations feed recurring or automated allocation, the evidence package should include:

1. **Purpose and decision level:** the business question and the granularity of decision the model is intended to support.
2. **Data and transformation record:** the sources, definitions, adjustments and coverage limitations associated with material inputs.
3. **Priors and external evidence:** the assumptions introduced from experiments, previous models or expert judgment.
4. **Validation:** backtesting, out-of-sample performance, sensitivity analysis and comparison with experimental or other causal evidence.
5. **Uncertainty and stability:** confidence around contribution and response estimates, together with evidence of how results change under plausible alternative specifications.
6. **Use boundaries:** the conditions under which outputs should not be used, including decisions outside the historical range represented in the data.

These requirements should become stronger as a model moves from directional discussion toward automated or recurring allocation. AI can make MMM easier to operate and interrogate; it does not remove the need to determine whether the model is causally informative and fit for the decision concerned.

Chapter 8.

Media Quality, Attention, and Machine-Readable Value

AI increases the operational importance of media-quality signals because optimization is constrained by the inputs available to the system. If inputs are limited to cost, impressions, completion, clicks, conversions or platform-reported outcomes, allocation will favor those measures. Adding validated evidence on attention, context, screen environment, sound, content quality, suitability, creative fit and longer-term outcomes can support richer objectives.

Relevant media-quality evidence must be defined for automated use without collapsing distinct attributes into one score. Trusted content environments, large-screen viewing, sound and motion, context, communal viewing, attention and brand effects represent different constructs and require methods appropriate to the decision being supported.

Automated systems can use only signals they can ingest, but ingestibility does not establish validity. Machine-readability is necessary for systematic use by AI; methodological credibility and commercial relevance require separate evidence.

From quality as narrative to quality as infrastructure

Historically, media quality has often been communicated through narrative. Publishers and platforms described the value of their content, environments, audiences, and viewing experiences. Agencies and advertisers evaluated those claims through judgment, research, historical experience, and negotiated trust.

Automated systems cannot systematically consider a quality claim unless the relevant evidence is represented in a form they can interpret. The required shift is not from narrative to data alone, but from unsupported or inconsistently expressed claims toward evidence that is defined, measured and documented well enough for its intended use. Human judgment and qualitative interpretation will continue to matter, particularly where value is contextual, strategic or difficult to reduce to a single metric.

Quality becomes infrastructure when defensible evidence can move reliably through the advertising workflow. This requires clear definitions, consistent measurement, usable formats and documented methods and limitations. Systems also need a way to carry that evidence into planning, activation and measurement, with governed access for models and agents. The objective is not to make every aspect of media value directly optimizable. It is to ensure that relevant evidence can inform decisions without losing the methodological context required to interpret it.

Standards work is addressing these requirements. The Media Rating Council's standards-development priorities for 2025–26 include attention, AI, cross-media measurement, data quality and non-probability supplements, as well as guidelines developed with IAB for direct biometric and indirect or signal-based attention measurement (Ivie, 2025, p. 3). Structured quality signals cannot support dependable planning, measurement or optimization when constructs are unclear, methods are materially inconsistent or users cannot determine the conditions under which evidence is valid.

The requirement is also economic. When automated systems lack credible evidence about context, attention, exposure environment or longer-term effects, they will place greater weight on signals that are easier to obtain and compare, such as price, delivery, completion or short-term conversion.

Contextual intelligence as inventory infrastructure

AI can also make the underlying content environment more legible to advertising systems. FreeWheel's Context Engine applies AI-based content recognition and classification within its Streaming Hub to support more granular contextual decision-making. FreeWheel positions the capability as a way to improve advertising relevance, strengthen brand safety and create additional monetization opportunities across premium video content.

The significance extends beyond conventional keyword targeting. In the Showcase, FreeWheel described a hypothetical use case in which an advertiser associated with a particular brand ambassador could identify ad opportunities following that person's appearance across a program, film or television interview. This illustrates how AI can translate the content of video into a continuously updated set of structured contextual signals.

For premium video, this is an important development. Content environment, adjacency, talent, themes, tone and suitability have historically been understood through schedules, genres, program metadata and human sales knowledge. AI-based contextual systems can create more granular and current descriptions of those environments, allowing approved attributes to become available to planning, suitability and execution workflows.

Contextual classifications describe content, not necessarily quality or effectiveness. Where classifications affect suitability, pricing or demand access, providers should disclose methods, latency, error rates, category definitions, sensitive-content treatment and challenge procedures. Performance or quality claims require separate validation.

Placement-level characteristics

A useful starting point is the concept of placement-level characteristics: screen size, sound-on likelihood, content genre, content quality, content adjacency, ad pod position, ad load and clutter, completion likelihood, viewability, attention, brand safety, brand suitability, contextual relevance, device environment, co-viewing likelihood, interactive features, creative-media fit, exposure duration, and format type. Not all of these characteristics will be relevant to every advertiser, outcome or decision, and several require different measurement methods rather than a common scoring system. Two impressions that look identical in a basic delivery report may differ materially in their exposure conditions and in their likely relevance to a particular campaign objective. Where decision systems treat such placements as equivalent despite credible evidence of consequential differences, optimization may favor lower-cost or more easily measured supply without recognizing those differences.

CIMM's Navigating Quality¹⁷ work frames placement-level characteristics – including prominence, context and exposure environment – as potentially important inputs to the valuation of TV advertising rather than merely secondary descriptors (CIMM, 2026b). For those characteristics to support planning, optimization or measurement, however, they must be defined and evaluated at the level appropriate to the use case. The task is not to convert every characteristic into a universal quality score, but to make defensible evidence available where it can improve a specific decision.

¹⁷ See CIMM, Quality Matters: Navigating Quality in Media Buying and Measurement (2026).

Exhibit: Minimum Context for a Machine-Readable Quality Signal

Field	Required information
Construct	The specific characteristic represented, such as attention, context, suitability, prominence or exposure environment
Source	The data, observation or model from which the signal was derived
Unit and population	The impression, creative, placement, household, person or other entity to which it applies
Observed or modeled	Whether the value is directly measured, inferred or predicted
Validation status	The evidence supporting reliability and relevance to the proposed use
Uncertainty and limitations	Known error, confidence, coverage constraints and limits on comparison
Permitted uses	Whether the signal is fit for planning, bidding, optimization, analysis or evaluation
Refresh and expiry	When the signal was produced and when it should be treated as stale

Making attention evidence usable in decision systems

Attention measurement extends analysis beyond whether an ad was served or viewable to whether the exposure had a reasonable opportunity to attract notice or influence response. It offers ways to move beyond the binary question of whether an ad was served or viewable toward questions about whether an exposure had a reasonable opportunity to attract notice or influence response.

Attention evidence may help differentiate exposure conditions and creative performance, but its appropriate use depends on what has been measured. Biometric observation, modeled attention, viewability-related proxies, creative diagnostics and platform-derived indicators do not necessarily represent the same construct or support the same decisions.

Where attention measures are sufficiently validated for a particular application, they can be structured for use in planning, creative assessment, pre-bid selection, in-flight analysis, MMM, attribution or outcome research. Each use requires the signal to retain its methodological context, including the source of the data, unit of analysis, validation basis, uncertainty and limits on comparability.

The desired shift is from isolated attention scores to validated evidence that people and systems can use within defined decisions. It is from isolated attention outputs toward validated evidence that people and systems can use appropriately within defined decisions.

“AI systems optimize to the inputs they receive, so attention needs to become one of those inputs. We cannot ignore the fundamental difference between an impression and human attention.”

Karen Nelson-Field, Founder and CEO, Amplified Intelligence

The Showcase demonstrated what this change of form can mean in practice. Attention has frequently been delivered through a proprietary dashboard as a summary score interpreted after a campaign has run. That format may be useful to a human analyst, but it is poorly suited to models and agents that require structured inputs before and during execution.

A generative-attention system presented during the event converted individual creative assets into reusable, second-by-second viewing datasets. The system analyzed frames, objects, faces, motion, text and narrative features within the creative, interpreted them against platform-specific viewing behavior and simulated approximately 20,000 viewing responses for each render. Its predictions were anchored in biometric ground-truth data collected across 21 markets and major media platforms.

Exhibit: Ground Truth and Scaled Truth in AI-Enabled Attention Measurement¹⁸

Ground truth, then scaled truth.

One validates. One scales. Together they make attention usable at system level.

Biometric measurement.

Provides the ground truth



Generative modelling

Scales that truth into structured datasets



The output was a structured profile of predicted active attention, passive attention and non-attention over time, together with platform benchmarks. It was a structured profile describing the predicted pattern of active attention, passive attention and non-attention over time, together with relevant platform benchmarks. The resulting data could inform pre-bid decisioning, creative development, an MMM, an AI model or a runtime constraint applied by an agent during planning or optimization.

¹⁸ Amplified Intelligence, CIMM AI Innovation Showcase, June 2026.

[illegible]

Attention is now infrastructure.

One ad uploaded. One dataset out. What you do with it is up to you.

The diagram illustrates four distinct use cases for attention infrastructure, each presented in a separate box. Each box follows a consistent format: 'IF YOU HAVE...' followed by a specific input, 'THEN' followed by the resulting action or outcome.

- A tag**
THEN
Align attention into your pre-bid stack.
- An MMM**
THEN
Improve model fit with attention seconds.
- An LLM**
THEN
Train it on attention as a feature.
- An agent**
THEN
Use attention as a runtime constraint.

AI and the Transformation of Advanced TV and Video Advertising and Media Measurement

Dependable generative attention estimates require recent, representative and validated human-observation data for training and testing. Generative systems should not be assumed to produce dependable attention evidence independently. Their value depends on the quality, recency, representativeness and validation of the human-observation data against which they are trained and tested²¹.

Creative media optimization and the blindness risk

AI can evaluate creative characteristics and media-environment signals together, allowing campaign teams to consider whether an asset is suited to the context, format and exposure conditions in which it will appear. This can improve scenario development, creative testing and campaign design.

The analytical requirement is to distinguish prediction from observation and association from causation. A modeled estimate of likely attention or emotional response is not equivalent to directly observed behavior. Nor does an association between a creative feature and performance establish that changing the feature will cause performance to improve. These signals may guide testing and bounded optimization, but their authority should reflect their validation and uncertainty.

Optimization blindness occurs when a system improves the metric it can see while degrading value it cannot see. In advanced TV and video, this may involve reducing CPM while weakening exposure quality, increasing completion without improving attention, favoring ID-rich supply over less addressable premium environments or prioritizing short-term response at the expense of longer-term effects.

The problem is not solved by adding more fields indiscriminately. Additional quality indicators can increase complexity, create opportunities for selective metric use and double count correlated characteristics. Decision systems require signals that are relevant to the advertiser's objective, sufficiently valid for the proposed action and accompanied by the context required for interpretation.

From machine-readable signals to decision-grade evidence

Machine-readable data is useful only when it is reliable and appropriate to the decision at hand. Decision-grade evidence requires a clear construct, a sound method, visible limitations and a defensible relationship to the outcome being evaluated or optimized.

For premium video, no single score can capture value across context, reach, attention, creative fit and short- and long-term effects. Structuring these signals for automated use should preserve their meaning and uncertainty rather than create false precision.

²¹ Amplified Intelligence presentation to the CIMM AI Innovation Showcase, June 3, 2026. Quantitative descriptions reflect the methodology presented by Amplified Intelligence.

Chapter 9.

Algorithmic Optimization in Streaming TV

Streaming TV combines sight, sound, motion, premium content and large-screen viewing with digital expectations for addressability, targeting, reporting and optimization. It is increasingly transacted programmatically, creating greater opportunity to apply the optimization capabilities long used in digital media. In 2026, an estimated 85-90% of CTV ad spending will be transacted programmatically²². Yet many advertisers are not taking full advantage of the optimization tools available in this environment, particularly when compared with online video.

Predictive bidding and allocation tools are already available. Their wider use in streaming TV depends on workflow integration, confidence in their decisions and measurement signals that are fit for purpose.

“Streaming TV is using algorithmic optimization far less extensively than online video. When it is used, advertisers can see material improvements in effective cost per reach, quality or outcome-based objectives. These optimizations can help advertisers balance driving stronger performance with increased workflow and budget efficiencies.”

Marissa McArdle, Senior Vice President, Streaming TV Product, DoubleVerify

Algorithmic optimization can evaluate more combinations of publishers, audiences, frequencies, creative variants and budget allocations than human teams can assess manually. Reducing the cost of evaluating these alternatives enables optimization to become more continuous, more granular and more responsive to changing campaign conditions.

DoubleVerify data presented during the Showcase illustrates the current adoption gap. Across campaigns with identifiable optimization objectives between May 2025 and May 2026, pre-bid algorithms accounted for 49% of relevant online-video revenue, compared with 21% of streaming-TV revenue. The gap appeared across each of the major KPIs examined, including CPM, reach, completed view, acquisition and viewability.

The objectives used for optimization also differed by channel. CPM represented 62% of the pre-bid algorithmic KPI mix in streaming TV, compared with 43% in online video, indicating a greater concentration on cost efficiency. Reach showed an especially large difference: pre-bid algorithms accounted for 75% of known-KPI online-video reach revenue, compared with 10% in streaming TV. For CPM-oriented streaming-TV activity, the corresponding algorithmic share was 36%, the strongest level among the streaming-TV KPIs shown.

“Quality CPM is not a fixed definition. If quality means viewability and completion to one advertiser, the system can optimize toward that. If it means attention and brand suitability to another, it can optimize toward those signals. The ‘Q’ is whatever matters to the client.”

Amanda Carlton, Vice President, DV Scibids AI Product, DoubleVerify

²² Based on industry consensus projections for 2026. See StackAdapt, A Complete Guide to CTV Advertising, projecting that over 84% of CTV ad spend is executed programmatically; and Adwave, Connected TV Advertising: 2026 Strategy Update, estimating automated and programmatic market share at 88%. This ecosystem is dominated by private marketplace (PMP) and programmatic direct deals, with open programmatic public auctions accounting for an estimated 18% to 19% of total spending (Paxlate/MediaPost, Study Finds More Than Half of CTV Programmatic Serving via Top 5 Supply Sources, 2025).

Why streaming TV has lagged online video

Streaming TV combines digital delivery with commercial and operational practices inherited from television, but its optimization environment is more constrained than that of conventional online video, for four main reasons:

1. A substantial proportion of premium video investment is transacted through upfront commitments, guaranteed deals, private marketplaces and other arrangements that limit the inventory or price variables an algorithm can alter.
2. Publishers, ad servers, SSPs, DSPs and measurement providers do not necessarily expose comparable data or operate with consistent definitions.
3. Important outcome signals may arrive too slowly or at insufficient scale to support rapid optimization.
4. Publishers may be reluctant to expose the pricing, yield or inventory information required for external systems to optimize freely across supply.

The incentives of buyers and sellers may also diverge. A buyer may seek lower cost, incremental reach or stronger outcomes; a publisher may seek yield, delivery against commitments, protection of scarce inventory and control over audience or content data. An optimization process that improves one party's objective may impose costs on the other unless the permitted variables and commercial rules are explicit.

Limited adoption reflects more than technological caution. It reflects restricted decision rights, incomplete evidence, heterogeneous supply paths and unresolved questions about whose objective the algorithm is authorized to pursue.

From fixed buying to dynamic value selection

Algorithmic optimization changes how media value can be assessed. Traditional buying often commits spend based on expected value at the time a deal or allocation is established. In biddable environments, algorithms can instead evaluate individual opportunities continuously and adjust bids or allocations according to the advertiser's objective.

For streaming TV, this can support a range of goals: lowering cost per impression, improving reach efficiency, managing frequency, increasing completion, prioritizing higher-quality supply, optimizing toward household reach or acquisition, improving publisher mix and reducing waste within PMP environments.

Exhibit: Reducing the Cost of PMP Streaming-TV Impressions through Custom Bidding²³

Case Study

Achieving A 23% Lower Cost Per Impression On PMP STV Campaigns

Context

A brand and its agency purchase a mix of PG and PMP STV inventory, with the agency focused on keeping PMP CPMs as close to the floor price as possible to maximize impressions.

By consolidating multiple publishers into a single deal, Scibids AI could selectively bid on the most efficient PMP impressions rather than being constrained by fixed PG buying.

Solution

Scibids provides custom bidding technology that helps advertisers maximise value from STV spend in biddable environments like DV360, with the goal of offsetting its own fees by reducing net CPM.

Since PG deals typically delivered at a \$40 CPM, Scibids was tasked with outperforming this through PMP buying, while the agency leveraged Scibids' fee-clearing functionality in DV360 to simplify financial reconciliation.

Results



After plug in, Scibids compressed cost to achieve a **23% lower cost per impression** in the remaining 32 days of the campaign inclusive of Scibids! **CPM -23%**

DV DoubleVerify

9

The objective should be defined by the advertiser's desired outcome rather than defaulting to the lowest available price. Depending on the campaign, value may mean incremental household reach, quality-adjusted exposure, completed viewing, attention, acquisition, business outcomes or an explicitly defined combination of these factors.

Custom bidding and quality-adjusted optimization

Custom bidding becomes particularly relevant because the definition of value varies by advertiser. One campaign may prioritize reach, another acquisition and another a combination of attention, exposure quality and frequency. A generic optimization objective may not adequately represent those differences.

Custom algorithms can instead incorporate the signals most relevant to a particular campaign objective. These may include viewability, audibility, attention, completion, brand suitability, content context, screen environment, ad load, frequency, incremental reach, outcome probability and supply-path quality.

This distinction matters because an algorithm optimized solely toward raw CPM or delivery may identify inexpensive impressions without capturing the broader value of the exposure. Quality-adjusted optimization creates the possibility of balancing price with the characteristics an advertiser considers important, provided those characteristics are clearly defined, measurable and available to the optimization system.

²³ DoubleVerify, CIMM AI Innovation Showcase, June 2026.

Exhibit: Selected Company-Reported Streaming-TV Optimization Results²⁴

Use case	Optimization objective	Reported result	Evidence status	Principal limitation
Private-marketplace streaming-TV campaign	Cost efficiency	23% reduction in cost per impression	Company-reported case study	Comparator and campaign conditions may not generalize
Quality-adjusted campaign	Quality-adjusted CPM and reach	52% reduction in quality-adjusted CPM and doubled unique reach	Company-reported case study	Result depends on the definition and validation of “quality”
Outcome-oriented campaign	ROAS and acquisition	23% increase in ROAS and 66% reduction in CPA	Company-reported case study	Outcome data, attribution method and control design affect interpretation
Reach-focused campaign	Incremental household reach	847,000 additional households and approximately \$125,000 in reported efficiencies	Company-reported case study	Incrementality and control methodology require assessment
Premium video subscriber campaign	Cost per acquisition and conversion	25% lower CPA and 58% higher conversion	Company-reported FreeWheel case study	Single selected application; not an independently audited benchmark

These cases illustrate how predictive optimization can be applied against different objectives, including cost efficiency, quality-adjusted reach, acquisition and household reach. Reported results include reductions in cost per impression and quality-adjusted CPM, increased reach and improvements in ROAS and CPA. They demonstrate operational possibility rather than universal performance: campaign design, eligible inventory, data availability, optimization objective, attribution method and control methodology can all materially affect results. Their significance is therefore not that algorithms will reproduce the same gains in every campaign, but that predictive optimization is already capable of influencing cost, reach and business outcomes in streaming-TV workflows.

These results demonstrate operational possibility rather than universal performance. Campaign design, eligible inventory, data availability, optimization objective, attribution method and control methodology can all materially affect results. Their significance is therefore not that algorithms will produce the same gains in every campaign, but that predictive optimization is already capable of influencing cost, reach and business outcomes in streaming TV workflows.

In one DoubleVerify case study, an advertiser and its agency used custom bidding across PMP streaming TV inventory to select more efficient impressions across multiple publishers. Over the remaining 32 days of the campaign, the company reported a 23% reduction in cost per impression, inclusive of the optimization fee.

“Outcome-based optimization is not only about media efficiency. It is about identifying what is actually driving sales. The conversion data exists in CTV, but it is not yet being activated as extensively as it could be.”

Amanda Carlton, Vice President, DV Scibids AI Product, DoubleVerify

24 Sources: DoubleVerify and FreeWheel presentations to the CIMA AI Innovation Showcase, June 2026. Results have not been independently audited by CIMA.

Measurement requirements

Algorithmic optimization is only as useful as the signals available to guide it. If an algorithm is optimizing toward reach, reach must be measured credibly. If it is optimizing toward outcomes, the relevant outcome signals must be reliable. If it is optimizing toward quality, the underlying quality measures must be clearly defined and available. If it is allocating across publishers, those inputs must be sufficiently comparable to support meaningful decisions.

Measurement and optimization are interdependent. Better measurement expands the information an algorithm can use to distinguish value, while incomplete or biased measurement constrains the decisions it can make. An optimization system can be highly efficient within the information available to it and still produce a strategically suboptimal result if important dimensions of value are absent.

This is especially consequential in premium video. Cost and short-term response are comparatively easy to encode, while characteristics such as attention, context, incremental reach and exposure quality can be more difficult to represent consistently. If optimization systems are given only cost or short-term performance signals, they may undervalue inventory whose benefits are not captured by those measures.

Accountable optimization therefore requires objectives and inputs that are measurable, reviewable and aligned with the advertiser's strategy. The opportunity is not simply to automate bidding more extensively in streaming TV, but to use richer and more defensible signals so that automation optimizes toward the outcomes advertisers actually value.

Chapter 10.

Composable Data Infrastructure for People and Agents

AI value depends as much on data and workflow infrastructure as on model capability. Useful recommendations require access to trusted data, consistent metadata, business rules and operational systems. Connected infrastructure supplies permissions, taxonomies, identity, clean rooms, APIs, governance and audit logs so that AI outputs can be translated into enterprise action. Without it, AI remains an isolated application.

Data infrastructure and market infrastructure are related but not identical. Data infrastructure determines whether an organization can supply reliable inputs, control access and trace use. Market infrastructure determines whether multiple organizations and systems can interpret those inputs, interact through compatible interfaces and allocate responsibility when decisions cross organizational boundaries. A company may be internally AI-ready while the wider transaction or measurement environment remains institutionally unready.

This is especially important in advanced TV and video because the relevant data is distributed across many organizations. Advertisers hold first-party customer and business data. Publishers hold exposure and inventory data. Platforms control transaction and delivery data. Measurement providers hold performance and attribution data. Identity providers connect signals. Retailers and commerce partners hold outcome data. Agencies coordinate strategy and execution.

Privacy regulation and platform changes have scattered data across disconnected systems, making consistent cross-channel measurement more difficult (IAB & BWG Global, 2026, p. 3). The problem is directly applicable to advanced TV and video: the constraint is not simply model sophistication, but the inability of fragmented data environments to support consistent, trusted, cross-channel decision-making.

Composability addresses simultaneous demands for monetization, privacy, rights protection and AI-enabled efficiency by allowing organizations to modernize selected capabilities without replacing the entire operating environment.



From data availability to agentic control

At the Showcase, Snowflake presented a three-stage path from data availability to governed AI-enabled action: unification, contextualization and action. The model comprises three successive capabilities: unification, contextualization and action. Rather than measuring organizational maturity in general, it describes the sequence of capabilities required for AI systems to move from accessing data to supporting governed operational decision-making.

Exhibit: From Data Unification to Governed AI-Enabled Action²⁵

Stage	Primary Objective	Key Capabilities	Illustrative TV & Video Applications
1. Unification	Bring together relevant enterprise data and make it available for secure collaboration.	• Structured and unstructured data integration • Cloud and on-premise connectivity • Clean rooms and secure data sharing • Controlled data access	Impression and campaign data, audience data, content metadata, publisher signals, outcome data
2. Contextualization	Add organizational meaning so AI systems can interpret data consistently and correctly.	• Ontologies and semantic models • Business rules and policies • Taxonomies and metadata • Governance and permissions	Standardized audience definitions, quality signals, measurement rules, privacy policies, commercial constraints
3. Action	Enable AI agents and enterprise applications to use governed data to support operational decisions.	• Agent orchestration • Workflow automation • Enterprise applications • Decision support	Measurement, planning, forecasting, automated metadata enrichment and content tagging, campaign activation, in-flight optimisation, rights and royalty management, and content and streaming analytics

This architecture addresses one important component of organizational readiness: whether enterprise data can be unified, interpreted consistently and used within governed workflows. The broader AI Readiness Checklist in Appendix B also addresses business objectives, measurement fitness, delegated authority, auditability, privacy, interoperability, organizational ownership and ongoing evaluation.

Coordinating these stages is an agentic control plane. Rather than representing another data layer, it orchestrates how foundation models, enterprise data, applications, permissions and execution pathways interact. In a measurement workflow, for example, the control plane could combine impression data with outcome signals, enrich those observations with contextual information, make the resulting evidence accessible through a natural-language interface and return approved recommendations directly into activation systems, while maintaining appropriate governance throughout the process.

Durable competitive advantage is likely to depend less on access to widely available models than on proprietary data, contextual knowledge, business rules and the enterprise applications agents can coordinate.

25 Snowflake. Presentation to the CIMA AI Innovation Showcase, 3 June 2026.

“Agents are only as useful as the data they can draw on. When a publisher’s audience signals, inventory attributes, and measurement outputs live in separate systems, the agent negotiates blind. The sell side needs the same AI-ready foundation the buy side already has, with privacy and yield protection built in from the start, and no lock-in to a single model. Models are going to keep changing. The governed data underneath them shouldn’t have to.”

Erin Foxworthy, RVP Industry Principal, Marketing & Advertising, Snowflake

Unification makes data easier to combine. Contextualization makes it easier to interpret. Action turns the resulting insight into execution.

From data movement to data collaboration

Historically, many advertising workflows depended on moving data between parties. Files were transferred, matched, transformed, uploaded, downloaded, and reconciled. This created friction, privacy risk, cost, latency, and governance complexity.

Modern data collaboration is moving toward more controlled approaches. Clean rooms, cloud environments, zero-copy architectures, and permissioned collaboration frameworks allow partners to analyze and activate data while reducing uncontrolled movement. This shift is essential for AI.

In measurement, the practical value of this architecture lies in its ability to connect evidence that would otherwise remain distributed. LiveRamp’s cross-media model, for example, is designed to connect data across cloud environments and sources ranging from upper-funnel surveys and third-party sales information to television exposures, social platforms and complex retail-media networks. Zero-copy connectivity does not eliminate the need for identity resolution, permissions, quality assurance or methodological reconciliation. It reduces the repeated movement and duplication of underlying data, allowing approved analytical processes to operate closer to the environments in which the data is governed. This can shorten processing cycles and reduce privacy and security exposure, while preserving enterprise and publisher control.

People and agents as users

Media systems must serve both people and agents. Human users need interfaces, dashboards, explanations, controls, approvals, visualizations, and strategic context. Agents need structured data, APIs, permissions, machine-readable metadata, tool access, execution rules, and logs.

This dual-user environment will reshape system design. A platform may need to expose capabilities through both human interfaces and agent-accessible APIs. A measurement provider may need to provide both a human-readable report and an agent-readable results feed. A publisher may need both a sales narrative and a machine-readable inventory description.

AI-enabled access to audience data points toward the same design future. Generative AI can produce automated summaries of results and allow users to interrogate data through natural-language interfaces rather than complex queries, although chatbot-based data collection remains limited for complex audience research (Vanheuverzwyn & Rosanvallon, 2026, pp. 38–40). AI can improve access and interpretation, but the underlying measurement design still requires human governance, domain expertise, and methodological discipline.

The agentic workspace

One orchestration model demonstrated during the Showcase was the agentic workspace. Rather than requiring users to move repeatedly among dashboards and applications, the workspace brings together the files, knowledge sources, connectors, reusable skills, workflows and outputs associated with a defined business problem. It can retain context over time, apply a consistent set of instructions and support collaboration across a team.

Connectors are central to this model. For an agent to perform work across planning, activation and measurement systems, it must be able to access approved functions within those systems. In practical terms, the agent needs a governed equivalent of the capabilities currently available to an authorized human user. Where standardized interfaces are available, they can be integrated directly. Where they are not, organizations may continue to rely on proprietary integrations, reinforcing the importance of common agent-access protocols.

The model also establishes an important governance principle: delegation does not transfer ownership. An organization may delegate research, analysis, campaign configuration or optimization to an agent, but it remains accountable for the instruction, the permissions granted, the resulting action and its commercial consequences. Agentic interfaces should make delegation visible and controllable rather than disguising it as autonomous system behavior²⁶.

Knowledge and memory governance

Governance must extend beyond the data an agent may access and the actions it may execute to the context it is allowed to retrieve, retain and reuse. Agentic workspaces can combine enterprise knowledge, connected application data, conversation history, reusable instructions and persistent context. These sources should not automatically inherit identical permissions or retention rules. Retrieval should respect the authorization attached to the underlying source; access should be revocable; and material outputs should preserve sufficient information about the knowledge and instructions that informed them.

Persistent agent memory creates a related requirement. Organizations should define whether context may be retained, for how long, for which user, client, workspace and purpose, and whether it may influence subsequent workflows. Persistent instructions and policies should be versioned and auditable, and deletion or suppression requirements should propagate to retained context where applicable. Access to information should not automatically imply permission to preserve it indefinitely in agent memory.

The role of clean rooms

Clean rooms are likely to become more important as AI adoption grows. They provide environments where advertisers, publishers, platforms, retailers, and measurement partners can collaborate on sensitive data under defined rules. They can support matching, measurement, audience creation, outcome analysis, and model execution while reducing uncontrolled data exposure.

Clean rooms allow approved models or queries to operate across distributed data under defined rules for access, matching, outputs and movement. They improve control and auditability but do not establish the accuracy of identity, compatibility of definitions, sufficiency of permissions or causal validity of outputs. Those evidentiary and legal questions require separate assessment.

In AI-enabled workflows, clean rooms may support audience discovery, identity matching, exposure and outcome measurement, retail media collaboration, publisher-advertiser analytics, MMM inputs, incrementality analysis, model training or calibration, agentic measurement workflows, and privacy-safe optimization.

26 StationOne and Kochava presentation to the CIMA AI Innovation Showcase, June 3, 2026.

Composability and enterprise control

Enterprises increasingly seek to operate AI within their own cloud, clean room or governed collaboration environment, retaining control over permissions, linkage thresholds, output policies and partner access.

“The value will not come from more dashboards or more cuts of the data. It will come from moving repetitive planning, launching, measurement and optimization work into agentic systems, so that people can think about the information and keep their hands on the steering wheel.”

Hamilton Radcliffe, Head of Product, StationOne and Atlas Performance, Kochava

A composable system allows organizations to assemble capabilities from multiple providers while maintaining governance. This is especially important in advanced TV and video because no single vendor can solve every problem.

Composability nevertheless requires more than the availability of interchangeable technical components. It depends on three conditions operating together: a unified control plane through which data, models, applications and agents can be managed; governance embedded at the core of the architecture rather than added separately to individual applications; and enterprise interoperability that allows approved capabilities to work across clouds, proprietary systems and external partner environments. Without these conditions, modularity can reproduce fragmentation rather than resolve it, leaving organizations with a larger collection of tools but no consistent way to control permissions, apply policy or reconstruct how decisions were made.

The objective is controlled interoperability: connect data products, applications and agents while retaining authority over access, permitted uses, commercial rights and outputs. Organizations should be able to connect data products, applications and agents across an ecosystem while retaining authority over access, permitted uses, commercial rights and outputs. This allows collaboration and innovation to expand without requiring enterprises or publishers to surrender control of the underlying data and intellectual property from which their differentiation derives.

Data provenance, lineage and quality

As AI systems consume more data, provenance becomes critical. Provenance means knowing where data came from, how it was created, when it was refreshed, what transformations were applied, what permissions govern it, and what limitations apply. Lineage means being able to trace how data moved through systems and how it influenced outputs.

Errors in AI inputs can recur through optimization, budget allocation and model training rather than remaining confined to a single report. It may train future models, shape optimization, alter budgets, and affect commercial outcomes.

Scaled AI deployment requires a composable operating architecture and operating model that connect data, models, workflows, governance and human oversight (World Economic Forum & Accenture, 2026, pp. 3, 36–38).

Chapter 11.

Commercial Models and Institutional Change

AI will not only change tools. It will change commercial operating models. The advertising market is organized around human workflows: client teams, planning teams, activation teams, operations teams, sales teams, yield teams, analytics teams, measurement teams, data teams, and technology teams. AI will affect how each of these functions works and how value is created between them.

Some tasks will become cheaper. Some workflows will become faster. Some roles will become less manual. Some forms of expertise will become more valuable. Some commercial relationships will be reorganized around systems rather than people.

This is why AI adoption should be understood as operating-model redesign rather than simple automation. Successful transformation involves shifts toward real-time orchestration, adaptive rules, end-to-end journey governance, and redesigned roles focused on thresholds, decision patterns, and human-AI collaboration (World Economic Forum & Accenture, 2026, pp. 7–13, 36–38). In advertising, the same logic applies to media planning and measurement: AI becomes transformational only when organizational decision rights, workflows, incentives, and governance adapt with the technology.

Advertisers: from media buying to decision architecture

Advertisers need a decision architecture that defines business objectives, optimization priorities, acceptable trade-offs, measurement requirements, data permissions, brand-safety rules, privacy constraints, approval thresholds, model-governance standards and partner accountability. AI can help advertisers evaluate scenarios, connect media to business outcomes, interpret measurement, refine audiences, generate creative variants, and optimize spend.

But the greatest value will come from using AI to create better decision architecture: the structure through which decisions are made. Advertisers will need to define business objectives, optimization priorities, acceptable trade-offs, measurement requirements, data permissions, brand safety rules, privacy constraints, human approval thresholds, model governance standards, and partner accountability requirements.

Advertisers that do not define these rules may find that AI systems optimize toward default platform objectives rather than advertiser business strategy.

Advertisers may also resist greater methodological complexity. More signals, models and quality indicators do not automatically produce better decisions; they can increase cost, create conflicting recommendations and make accountability harder to assign. The burden should remain on providers to demonstrate that an additional signal materially improves planning or performance, rather than merely expanding the number of available metrics.

Agencies: from execution layer to orchestration layer

Agencies face a shift from manual coordination toward orchestration. As AI automates planning, trafficking, reporting and optimization tasks, agency value moves toward strategy, governance, model interpretation and accountability.

Agencies can become orchestration partners because their role spans business objectives, media strategy, activation, measurement and partner accountability – functions that no single platform agent can represent independently. They can help clients design AI-enabled workflows, select tools, govern agents, interpret model outputs, evaluate measurement quality, ensure premium video value is represented, and manage the relationship between business strategy and automated execution.

Publishers: making value legible without losing control

Publishers and media owners need to make their inventory legible to AI systems without surrendering commercial control or reducing premium video to commodity impressions. As buyer agents become more capable, they will need to evaluate inventory through structured information. Publishers whose relevant value attributes are absent from planning and optimization inputs may be overlooked or undervalued because automated systems cannot assign weight to evidence they do not receive. Publishers will be better positioned where they can provide structured, appropriately validated information about context, exposure conditions, audiences, reach, outcomes and transaction rules, while preserving the methodological qualifications and commercial controls associated with those signals.

Publishers are likely to resist requirements that expose granular inventory, audience or pricing information if those disclosures weaken yield management, facilitate disintermediation or allow buyer systems to reverse-engineer commercial strategy. The appropriate objective is controlled legibility: sufficient information for evaluation and transaction, delivered through permissions and aggregation rules that protect proprietary data and seller discretion.

Controlled legibility distinguishes interoperability from disclosure. A buyer or agent may need enough information to establish eligibility, compare relevant attributes and execute an agreed transaction without receiving the granular data required to reconstruct a publisher's pricing, audience or yield strategy.

Publisher enablement represents a distinct opportunity within AI-enabled advertising. Outcome capabilities have often been used principally to demonstrate performance after delivery. A more operational model can connect publisher exposure, audience and inventory data with advertiser-approved outcome evidence in a clean room or other governed collaboration environment, allowing findings to influence packaging, audience strategy, inventory selection or optimization while future campaign decisions remain changeable.

This does not require unrestricted sharing of advertiser or publisher data. A publisher can make approved outcome signals, segment-level findings or optimization recommendations available while retaining control over raw event data, audience assets, pricing logic and yield strategy. Where the resulting claim concerns incrementality rather than association, experimental or other credible causal evidence remains necessary.

Atlas Performance by Kochava illustrates this emerging sell-side model. Kochava describes the system as connecting advertiser outcome data with publisher-side measurement, audience intelligence, optimization and incremental-lift analysis, with StationOne providing an AI orchestration layer. As with other company examples in this report, these capabilities should be understood as illustrative and company-reported rather than as independent CIMA validation. The broader market implication is that publishers can use AI and governed data collaboration not only to report outcomes, but to make outcome evidence operational while retaining control over commercially sensitive data and decision rights.

Platforms, measurement providers, data and identity providers

Platforms and ad tech companies are likely to become the operating environments through which many agents act. Ad servers, SSPs, DSPs, clean rooms, data collaboration platforms, measurement systems, and cloud environments may all expose agentic capabilities.

For platforms, this creates a strategic choice between supplying proprietary AI applications, enabling external intelligence, or combining the two. FreeWheel's "Built In, Build On" strategy illustrates the hybrid approach. The platform supplies native forecasting, optimization, planning and troubleshooting capabilities, while also exposing selected data and functions through APIs, partner tools and agent infrastructure so that customers can apply their own models and workflows.

This may produce a different source of platform power from the conventional walled-garden model. The platform does not need to own every agent or every decision model. It can become more central by serving as the secure execution environment through which multiple agents operate. Its commercial value may increasingly derive from the quality of its transaction data, reliability, interoperability, permissioning, developer ecosystem and ability to execute approved actions at scale.

The same logic may extend to enterprise-data ecosystems. Data products, analytical applications and specialized agents may increasingly be distributed or commercialized through governed collaboration environments rather than delivered as conventional standalone software. This could allow publishers, agencies, measurement providers and specialist technology companies to make proprietary capabilities available to partners while retaining control over the underlying data, permitted functions and commercial terms.

The model could also alter partner economics. Agencies and publishers may build differentiated intellectual property without recreating the underlying ad-serving and transaction infrastructure. Platforms may generate greater usage and integration depth while allowing clients to preserve their own strategy. However, the balance is delicate. External-agent access can still create dependency when access terms, permitted functions, data availability or interoperability are controlled unilaterally. Evaluation should cover the practical scope, portability and governance of access, not merely whether an API exists.

Measurement providers have historically played the role of scorekeeper, evaluator, or validator. In an AI-enabled market, they may increasingly become decision-support infrastructure. Their outputs will feed planning, buying, optimization, MMM, reporting agents, and potentially automated allocation systems.

Data and identity providers will need to prioritize quality, provenance, interoperability, and governance. In earlier phases of digital advertising, the market often rewarded scale. In AI-enabled environments, scale remains useful, but fidelity becomes more important.

Distribution of costs, benefits and bargaining power

AI is unlikely to distribute economic value evenly across the advertising ecosystem. Organizations that control transaction data, execution environments, identity infrastructure or widely used interfaces may gain strategic influence because external agents depend on access to their systems. Equally, organizations with distinctive first-party data, trusted premium inventory or proprietary decision logic may strengthen their competitive position, provided they can connect those assets to emerging AI infrastructure without relinquishing commercial control.

Control over data access, inventory discovery and platform functions will shape bargaining power. An interface may appear open while access terms, data fields, rate limits, certification requirements or portability restrictions preserve substantial platform influence. Conversely, unrestricted access can compromise security, privacy and publisher control. The appropriate objective is contestable interoperability: legitimate competition and innovation supported by proportionate controls over data use, security, contractual performance and commercial rights.

Contestable interoperability means more than the existence of an API. It requires that qualified participants can discover relevant functions, obtain access on reasonable and non-discriminatory terms, move permitted data and decision logic between environments, understand material restrictions, preserve audit records and exit or change providers without disproportionate cost. It does not require unrestricted disclosure or access. Security, privacy, publisher control and contractual rights remain legitimate constraints, but they should not be used selectively to foreclose competition or make portability impracticable.

AI will also redistribute costs as well as benefits. Advertisers and agencies may reduce manual planning and operational effort but incur new costs associated with governance, systems integration, model validation and ongoing AI supervision. Publishers may gain access to new demand while facing increasing pressure to structure inventory, metadata and evidence for automated evaluation. Measurement providers may become more strategically important as their outputs increasingly influence operational decisions, while simultaneously assuming greater responsibility for the quality, transparency and appropriate use of those outputs. Standards, contracts and governance frameworks should allocate responsibility to the parties best placed to manage each category of risk, rather than assuming that automation removes operational cost.

Implementation capacity is also likely to differ significantly across the market. Large platforms, technology providers and agency groups can invest in APIs, agent authentication, security, model governance and standards development at a scale that may be difficult for smaller publishers, local media companies and independent agencies to match. Seemingly neutral technical standards can create unintended barriers to entry if compliance is costly or if dominant platforms effectively control the reference implementation.

The market should evaluate AI infrastructure by its effects on efficiency, competition, switching costs, data portability, bargaining power and the ability of smaller participants to connect, compete and challenge automated decisions. The long-term objective should be interoperability that broadens market participation, rather than interoperability that merely reinforces existing centers of platform power.

Stakeholder implications

The growth of AI-enabled planning, measurement and execution systems is likely to affect stakeholder groups differently:

- **Advertisers** may value lower operating costs, broader scenario evaluation and stronger links between evidence and action. They may resist opaque delegation, dependence on proprietary systems and unclear liability for automated expenditure.
- **Agencies** may benefit from shifting resources from manual execution toward strategy, orchestration and governance. Automation may also place pressure on labor-based remuneration, require investment in proprietary operating systems and create questions about ownership of agent logic, conflicts of interest and responsibility for error. Agency transitions may also be constrained by commercial models as much as by technology. Where remuneration remains tied to labor hours, staffing structures or execution volume, automation can reduce the activity on which fees have historically been based before new value-based models are established. Agencies and clients will need to determine how proprietary agents, workflow intellectual property, governance services and performance accountability are priced. They will also need to address conflicts where an agency-owned system recommends inventory, data or technology supplied by an affiliated business.
- **Publishers** may benefit from new sources of demand, more efficient transactions and better representation of premium inventory. They may resist requirements that expose sensitive pricing, audience or yield information, reduce negotiating discretion or make differentiated inventory appear interchangeable.
- **Platforms** can become more valuable as secure execution environments for multiple agents. Their control over interfaces, permissions, certification, rate limits and available data may nevertheless increase dependency even where the ecosystem is described as open.

- **Measurement providers** may become more operationally central as their outputs influence allocation decisions. This creates commercial opportunity but also increases their responsibility for methodology, uncertainty, neutrality and the consequences of inappropriate use.
- **Smaller publishers, local media companies and independent agencies** may benefit from lower workflow costs but may face disproportionate integration, security, certification and compliance burdens. Standards and access arrangements should be evaluated partly by whether they broaden effective participation or reinforce existing concentrations of technical capacity.
- **Standards bodies and assurance organizations** will be expected to distinguish between interoperability questions, which may require common technical approaches, and methodological or commercial questions that should remain subject to enterprise choice, contracts or independent evaluation. They may face pressure from participants seeking to turn proprietary practices into de facto market standards.
- **Regulators and enforcement agencies** are likely to focus on privacy, misleading claims, discriminatory effects, market foreclosure and the allocation of responsibility where automated decisions cross organizational boundaries. Their concern will be the function and consequence of the system, not simply whether it is described as AI.
- **Consumers, data subjects and creative rights holders** may benefit from more relevant advertising and lower production costs, but they also bear risks associated with data inference, synthetic representation, opaque targeting and the unauthorized use of creative material or likeness. Their interests should be reflected in permissions, disclosure, complaint and redress mechanisms.

Institutional risk: fragmentation at machine speed

AI could also deepen fragmentation. If each major platform, agency holding company, publisher, and ad tech provider builds proprietary agents with limited interoperability, the market may become harder to navigate. Instead of human teams coordinating across fragmented systems, agents will coordinate across fragmented systems – but without necessarily solving the underlying fragmentation.

Standards, governance and interoperability are commercial design choices, not merely technical ideals. They will influence which systems can participate, which parties retain control, how easily buyers and sellers can change providers, and whether proprietary innovation reduces coordination costs or simply transfers fragmentation into a machine-mediated environment.

“AI does not have to be right all the time to be valuable. The right standard is better, not perfect: is the system producing a better result than the process it replaces?”

Hamilton Radcliffe, Head of Product, StationOne and Atlas Performance, Kochava

Enterprise experience also shows a gap between AI pilots and production deployment. Legacy systems, siloed data, weak integration and limited workflow embedding can prevent capable models from generating operational value (Neptune Software, 2026, pp. 2–3).

Moving from AI pilots to production also requires less visible organizational capabilities: clear product ownership, integration with legacy systems, operational testing, release governance, customer support and processes for retiring unsuccessful capabilities. The execution gap is institutional as much as technical. Organizations may possess capable models but still fail to generate value if decision rights, data access, workflows and accountability remain unchanged.

Chapter 12.

Governance, Transparency, and Market Integrity

Governance enables adoption by bounding what systems may do, making actions observable and assigning responsibility for outcomes. Controls should be designed into automated workflows rather than added after deployment.

Senior executives will not delegate material decisions to AI systems they cannot understand, control, audit, or explain. Advertisers will not allow agents to spend significant budgets without clear permissions. Publishers will not expose inventory, pricing logic, or data assets without protections. Measurement providers will not want their outputs used in automated decisions without methodological context.

Governance is what allows AI to move from experimentation to trusted operation. The broader AI evidence base supports this conclusion. Responsible-AI practices are not keeping pace with model capability: documented AI incidents increased to 362 from 233 in 2024, while leading developers continue to report capability benchmarks more consistently than responsible-AI benchmarks (Sajadieh et al., 2026, p. 9). For advertising, the lesson is direct: as AI systems become more capable of acting within commercial workflows, governance must become more operational, not less.

The governance questions AI forces the market to answer

AI forces organizations to specify who defines audiences, validates signals, describes inventory, measures quality and selects outcomes. They must also decide who judges whether a model is reliable, when an agent may act and who answers for harm caused by its actions. These decisions become more pressing as systems move from recommendation to execution.

U.S. advertising AI is governed through multiple legal and institutional regimes rather than one framework. Privacy, consumer-protection, competition, intellectual-property, contract and anti-discrimination obligations depend on the data used, representation created, decision made and consequences. Organizations should assess obligations by function and use case: the same model creates different risks when summarizing a report, constructing a sensitive audience, generating a synthetic performer or committing expenditure.

Governance should be allocated to the right institutional level

These questions do not all require the same institutional response. Most decisions about objectives, budget limits and approval thresholds belong within the advertiser, agency, publisher or platform deploying the system. Responsibilities between trading partners should be addressed through contracts, service levels and audit rights. Technical interoperability problems may require industry standards. Claims concerning measurement validity, security or compliance may require independent assurance.

A workable governance framework should allocate each risk to the lowest level capable of managing it effectively:

1. **Enterprise governance** should define permitted uses, decision rights, risk classifications, human oversight and internal accountability.
2. **Contractual governance** should establish data-use restrictions, performance obligations, audit rights, liability, incident notification and remediation between counterparties.
3. **Technical standards** should support interoperable communication, agent identity, permissioning, status reporting and audit events.
4. **Independent assurance** should be used where one party cannot reasonably verify another party's claims and where error could materially affect trading, measurement or consumer rights.

Allocating governance by function avoids both over-centralization, which can slow low-risk experimentation, and reliance on enterprise self-governance for cross-company risks.

Data governance

Data governance is the foundation. AI systems should not have unrestricted access to all available data. They should access data according to defined permissions, purposes, legal constraints, contractual rules, and privacy obligations. Data governance should address what data can be used, why it can be used, who controls it, how it was collected, whether consent applies, how current it is, what transformations were applied, what outputs are allowed, whether data can be used for training, whether data can be used across clients or contexts, and how data is deleted, suppressed, or refreshed.

Model governance

Model governance addresses how AI and analytical models are built, validated, used, monitored, and explained. In advanced TV and video, model governance applies to predictive models, bidding algorithms, MMMs, attribution models, audience models, attention models, identity graphs, quality scores, optimization engines, and agentic decision systems.

Models should be used for purposes they are fit to support. A model built for directional planning may not be appropriate for automated budget reallocation. A quality score built for post-campaign analysis may not be ready for pre-bid optimization. An audience model built for prospecting may not be appropriate for measurement reconciliation.

Organizations should update model documentation, validation and permitted uses as data sources, models and workflows change. A static assessment can quickly become incomplete (Independent International Scientific Panel on AI, 2026, p. 6).

Security of agentic workflows

Agentic interoperability expands the operational attack surface. Systems that allow agents to discover tools, invoke functions and move across data environments must address authentication, authorization, prompt and tool injection, cross-tenant leakage, malicious or substituted connectors, excessive permissions and failures in third-party tools.

Security should be treated as an execution-layer requirement rather than a generic enterprise IT control. Minimum safeguards should include authenticated agent identities, least-privilege access, tool allowlists, transaction and budget limits, environment separation, verified connectors, continuous logging, anomaly detection, rapid revocation and tested recovery procedures.

Responsibility should also extend across chains of agents and tools. An organization should be able to identify not only the agent that initiated an action, but the external systems, models and connectors on which that action depended.

Agent governance

Agents differ from models because they can take actions. Agent governance must focus on authority. It should define agent identity, authorized users, data access rights, tools the agent can use, actions the agent can recommend, actions the agent can execute, actions requiring human approval, budget limits, campaign limits, client or brand constraints, logging requirements, escalation triggers, kill switches, error handling, and review processes. The market should assume that agentic permissions must be explicit, narrow, auditable, and revocable. Permissions should distinguish among retrieval, model context, persistent memory, tool use and execution: authorization to access a source for one workflow should not automatically confer authority to retain its contents, reuse them in another context or act on them beyond the permitted purpose.



A risk-based delegation model

Agentic authority should be assigned according to the risk and consequence of the action, rather than the apparent sophistication of the technology. The Delegation Model translates the paper's operating architecture into a decision-governance framework. The Five-Layer Stack identifies the systems and controls required for AI-enabled operation; the Delegation Model determines how far a system operating within that architecture should be permitted to move from information and recommendation towards execution.

The model distinguishes four tiers of authority. Responsibility may be delegated progressively, but the required controls become stronger as actions become more financially material, less reversible, more data-sensitive or more consequential for counterparties and consumers.

Exhibit: Risk-Based Delegation for Agentic Advertising

Tier	Authority	Illustrative action	Minimum control requirement
1	Informational assistance	Search, summarize, map or diagnose	Access controls, source visibility and quality checks
2	Reversible workflow configuration	Prepare plans, audiences, creative variants or campaign settings	Validation, versioning and human approval
3	Bounded execution	Adjust bids, pacing or allocation within approved ranges	Explicit limits, continuous monitoring, alerts and rapid reversal
4	Material commercial commitment	Commit significant spend, accept terms or use sensitive data	Affirmative authorization, enhanced audit, security and liability controls

The risk tier should be reviewed when the system, data, objective or market context changes. A workflow that is low-risk in a test environment may become materially different when deployed across multiple clients or connected to live expenditure.

Human oversight, auditability, privacy and standards

Different workflows require different oversight models. Human-in-the-loop workflows are appropriate where decisions are high value, high risk, novel, brand-sensitive, legally sensitive, or commercially material. Human-on-the-loop workflows may be appropriate for lower-risk optimization within defined thresholds.

Agentic infrastructure can also be assessed against three operational tests: flexibility, transparency and scalability. FreeWheel uses the same terms in its AI product strategy. They can also be treated as governance requirements:

- **Flexibility** concerns whether organizations can define their own objectives, models, data inputs and business rules rather than being required to adopt a platform's default optimization logic. Flexibility should nevertheless operate within explicit permissions and should not allow custom agents to bypass publisher rules, advertiser controls or legal obligations.
- **Transparency** concerns whether authorized users can understand the data, events, algorithms and outcomes informing an agent's recommendation or action. FreeWheel's published approach emphasizes visible data and observable results, but the market will need more precise definitions of what transparency means in practice: access to transaction-level evidence, documentation of models and objectives, records of agent actions, explanation of material recommendations and mechanisms for review or challenge.
- **Scalability** concerns more than computing capacity. Agentic infrastructure must support high transaction volumes, complex workflows and multiple partners without weakening security, consistency or auditability. A capability that works in a controlled demonstration may not be ready to manage live campaigns, contractual commitments and material expenditure across many clients and markets.

Platforms need to accommodate different agents while maintaining consistent controls for identity, function calls, status and action records. More customization can make those controls harder to secure and audit.

Material AI decisions must be reconstructable. Records should identify the use case, objective, system, model version, authorized user and agent. They should also preserve data sources, permissions, material assumptions and uncertainty, the recommendation and action, the applicable approval or rule, the time, the outcome, and any exception, override or correction.

Not every participant requires access to every underlying input or proprietary model. The record should nevertheless be sufficient for authorized parties to reconstruct the decision, establish responsibility and investigate a dispute.

Organizations can apply these governance principles to individual use cases through the AI Readiness Checklist in Appendix B.

Principles for trusted AI infrastructure

Govern the decision, not the label applied to the technology: Requirements should reflect what a system does, the information it uses and the consequences of its actions. The same underlying model may require different controls when used to summarize a report, alter campaign delivery or commit expenditure.

Match control to materiality, reversibility and risk: Low-risk informational assistance should not carry the same burden as actions involving sensitive data, contractual commitments or significant budgets. Oversight should increase as decisions become harder to reverse or more consequential.

Preserve commercial competition above common infrastructure: Shared definitions, interfaces, authentication methods and audit requirements should allow proprietary systems to interact. They should not determine prices, optimization strategies, commercial terms or a single model of market value.

Require transparency sufficient for responsibility and challenge: Market participants do not require unrestricted access to every model or proprietary input. They do require enough information about material objectives, evidence, permissions, actions and limitations to understand responsibility, evaluate fitness for use and contest disputed outcomes.

Make automated actions attributable and reconstructable: Material decisions should produce records showing which authenticated system acted, under whose authority, using which permitted data and constraints, and with what result. Auditability must extend across connected systems rather than ending at the boundary of one vendor's platform.

Use standards where coordination is genuinely shared: Common approaches are most valuable where agents must identify themselves, discover capabilities, exchange defined information, invoke approved functions and preserve consistent records across organizations. Enterprise policy and contracts should remain the principal mechanisms for issues that are specific to one organization or commercial relationship.

Liability and redress

Auditability is necessary but not sufficient. Contracts and operating procedures should also define responsibility when an agent acts on incorrect data, exceeds its authority, misinterprets a campaign objective or produces a disputed commercial outcome. Relevant provisions may include responsibility for configuration error, unauthorized action, model failure, data-quality defects, delayed intervention and failures in a third-party tool invoked by the agent.

Buyers and sellers should have a practical mechanism to challenge material automated decisions. This may require access to a decision record, a named counterparty responsible for investigation, agreed response times and rules for correction, reimbursement or reversal. A market in which decisions can be automated but not effectively contested would shift risk toward the party with the least visibility into the system.

A practical dispute process should provide:

1. **Preservation of evidence:** relevant prompts, inputs, model and agent versions, permissions, recommendations, approvals and actions should be retained.
2. **Immediate containment where required:** the affected action or permission should be suspended where continued operation could increase loss or risk.
3. **Named responsibility:** one counterparty should be responsible for coordinating investigation and communication, even where several vendors or agents contributed.
4. **Defined response times:** contracts should specify notification, initial assessment and resolution periods proportionate to the seriousness of the incident.
5. **Investigation and challenge rights:** authorized parties should be able to inspect the decision record and identify which system, data or rule produced the disputed outcome.
6. **Correction and remediation:** available responses should include correction of data or configuration, reversal where feasible, reimbursement, re-performance, model or permission changes and measures to prevent recurrence.

Responsibility should follow control and capacity. The party best placed to prevent, detect or correct a category of failure should not be able to transfer all associated risk to a participant with less visibility or technical authority. Auditability explains what happened; redress determines what the parties can do about it. Trusted automation requires both.

Privacy governance should apply not only to the data stored in each system, but to the inferences and transfers created when agents operate across systems. An agent may have individually authorized access to several datasets while producing a combined use that was never intended or permitted. Controls should enforce purpose limitation at the level of the workflow, restrict the onward use of outputs, preserve suppression and deletion requirements across connected tools and prevent prompts, logs or intermediate results from becoming unauthorized training data.

Organizations should also maintain a clear record of which legal and contractual basis permits each material data use. Clean rooms and privacy-enhancing technologies can reduce uncontrolled data movement, but they do not determine whether a use is lawful, proportionate or consistent with consumer expectations.

AI governance in advanced TV will remain distributed across enterprise controls, contracts, standards, platform design, measurement practice and assurance. The test is whether these mechanisms together make systems transparent enough to assign responsibility, interoperable enough to coordinate and contestable enough to support challenge and redress.

Chapter 13.

Conclusion: Building Accountable Market Infrastructure

AI can lower the cost of planning and buying advanced TV, reduce manual reconciliation, connect measurement to decisions and help publishers present evidence about their inventory. The benefits depend on the quality of the information systems use and the authority they receive.

Incomplete identity can distort audience decisions. Inconsistent measurement can redirect budgets. Easily observed short-term outcomes can displace effects that take longer to measure. When these inputs feed execution systems, the same weakness can affect many decisions.

Organizations should begin with defined use cases, explicit baselines, evidence fit for the decision and bounded authority. They should expand that authority only after evaluating performance, errors, human intervention and unintended consequences.

Across the market, common technical work should focus on problems that companies cannot resolve alone, including agent identity, permissions, inventory and creative requirements, status reporting, action records and revocation. Objectives, pricing and proprietary optimization methods remain matters for commercial choice. Contracts should assign rights and responsibilities. Independent assurance has a role where material claims cannot otherwise be verified.

AI will give systems greater influence over what buyers can see and do. Dependable interfaces, credible evidence and clear decision rights will determine whether that influence widens access to premium video and improves decisions.

Appendix A.

Practical Questions for Senior Executives

1. Where is AI already being used in our planning, buying, activation, measurement, or optimization workflows?
2. Which AI systems are experimental, and which are already influencing real decisions?
3. Do we have a clear governance framework for AI use in media and advertising?
4. Who owns AI governance across media, measurement, data, privacy, legal, and commercial teams?
5. Do we distinguish between AI systems that recommend actions and AI systems that execute actions?
6. Can we audit AI-generated recommendations and actions?
7. Are our AI systems aligned with business objectives, or are they optimizing toward default platform metrics?
8. Are our campaign data, exposure data, and outcome data structured consistently enough for AI use?
9. Do we understand the provenance of the data used by AI systems?
10. Are identity assumptions documented?
11. Can our data be used safely in clean room or governed collaboration environments?
12. Are measurement outputs structured for the decisions they are intended to support, including in-flight optimization where methodologically appropriate?
13. Are attention, quality and MMM inputs documented, validated and fit for use?
14. Are model priors based on evidence?
15. What actions may agents recommend, configure or execute, and which require affirmative approval?
16. What budget, pacing, data-use and contractual limits apply?
17. Are agent actions authenticated, logged, reversible and subject to escalation?
18. Are we prepared for agentic standards-based workflows?
19. Can AI systems interpret the characteristics, evidence and transaction rules that distinguish our premium video inventory?
20. Do we maintain evidence libraries that support those representations?

Appendix B.

AI Readiness Checklist for Advanced TV and Video

The AI Readiness Checklist is the implementation component of the paper's analytical structure. It is not a general maturity model and does not assume that every organization should progress towards maximum automation. It is designed to help organizations assess whether a defined AI-enabled decision or workflow has the objectives, data, measurement, governance, technical infrastructure and organizational ownership required for responsible deployment.

The checklist should be applied at the level of the individual use case rather than used to assign a single readiness score to the organization as a whole. An organization may be ready to deploy AI for reporting or anomaly detection while remaining unprepared to authorize automated budget allocation, sensitive-data use or contractual commitment.

Unanswered questions should limit the scope, authority or exposure of a use case until the relevant evidence or controls are established.

1. Business objective

- Is the decision or workflow to be improved clearly defined?
- Is there a baseline against which the AI-enabled process can be evaluated?
- Are optimization objectives and acceptable trade-offs explicit?
- Is it clear when the system should not be used?

2. Data foundation

- Are source, ownership, permissions, freshness and permitted uses documented?
- Are campaign, creative, audience, inventory and outcome definitions sufficiently consistent?
- Are identity assumptions and linkage confidence understood?
- Can data lineage be reconstructed across systems?

3. Measurement fitness

- Is the measurement method appropriate to the decision being made?
- Are uncertainty, limitations and coverage gaps visible?
- Are outputs timely and structured enough for the proposed workflow?
- Has the risk of using short-term or easily observed signals as proxies for broader value been assessed?

4. Authority and oversight

- Does the system advise, configure or execute?
- Which actions require affirmative human approval?
- Are budget, pacing, targeting, data-use and contractual limits explicit?
- Are escalation, suspension, reversal and kill-switch procedures defined?

5. Transparency and auditability

- Can the organization reconstruct the material inputs, recommendation and action?
- Is the acting system authenticated?
- Are model purpose, material assumptions and known limitations documented?
- Can users or counterparties challenge a disputed output or action?

6. Privacy, security and legal review

- Are purpose limitation, minimization, consent and opt-out requirements enforced?
- Are sensitive data and generated content appropriately controlled?
- Are clean-room or collaboration outputs subject to defined policies?
- Do contracts allocate responsibility for error, unauthorized action and data misuse?

7. Interoperability and portability

- Does the use case depend on cross-company definitions or interfaces?
- Are integrations based on documented, governed access rather than unrestricted connectivity?
- Can permissions be narrowed or revoked?
- Can the organization change providers or export relevant records without unreasonable friction?

8. People and operating model

- Is ownership assigned across business, technology, measurement, privacy and legal functions?
- Have approval processes and decision rights been redesigned for the new workflow?
- Are users trained to interpret outputs and manage exceptions?
- Does senior leadership understand the commercial and governance implications?

9. Evaluation and monitoring

- Are performance, error rates and human interventions measured?
- Is the system monitored for drift or changes in data and market conditions?
- Are unintended effects assessed, including effects on quality, representation and partner outcomes?
- Are permissions and risk classifications reviewed after material changes?

Appendix C.

AI Use Case Matrix

Creative Generation

AI can generate scripts, images, video assets, voiceovers, storyboards, translations, format adaptations, and creative variants. Potential benefits include lower production cost, faster iteration, improved localization, more creative testing, and expanded access to video advertising for smaller advertisers. Risks include inaccurate claims, poor creative quality, brand inconsistency, synthetic media concerns, legal exposure, and weak review processes.

Campaign Planning

AI can read briefs, extract objectives, recommend audiences, forecast reach, suggest publisher mixes, generate plans, and model scenarios. Benefits include speed, broader option generation, improved consistency, and better connection between objectives and plan structure. Risks include overreliance on opaque recommendations, incomplete inventory evaluation, weak quality inputs, and misalignment with business strategy.

Audience Creation and Proximity Targeting

AI can translate natural-language descriptions, behaviors, first-party data, location data, and contextual signals into audience segments. It can identify real-world locations, define trade areas, estimate household reach, and generate activation-ready audiences. Benefits include faster segmentation, local relevance, stronger links to physical commerce, and more dynamic audience strategy. Risks include weak identity assumptions, overbroad segments, privacy issues, and unclear provenance.

Agentic Buying

AI agents can interpret goals, discover inventory, communicate with systems, configure campaigns, prepare transactions, and recommend or execute optimizations. Benefits include workflow compression, faster activation, reduced manual burden, and improved responsiveness. Risks include unauthorized actions, opaque decisioning, financial exposure, weak auditability, and standards fragmentation.

AI-Powered Measurement

AI can map data, QA inputs, interpret results, detect anomalies, summarize insights, and recommend actions. Benefits include faster time to insight, reduced operational burden, and stronger links between measurement and optimization. Risks include automated misinterpretation, false precision, incomplete data, and opaque methodology.

MMM and Outcome Modeling

AI can support model operation, scenario planning, output interpretation, data preparation, and integration into planning workflows. Benefits include faster analysis, improved accessibility, stronger planning integration, and better outcome orientation. Risks include weak inputs, poor priors, model drift, overinterpretation, and underrepresentation of premium video.

Attention and Quality Optimization

AI can classify exposure environments, estimate attention, evaluate creative-media fit, and optimize toward quality-adjusted outcomes. Benefits include better representation of premium video value, improved planning, and more meaningful optimization. Risks include inconsistent quality definitions, overreliance on single scores, and limited comparability.

Synthetic Data and Synthetic Populations

AI and statistical modeling can be used to generate synthetic data, synthetic audiences, persona bots, digital twins, or synthetic populations to support imputation, data boosting, rare-audience analysis, privacy preservation, and source reconciliation. These techniques may be valuable in audience measurement and MMM, particularly where observed data is sparse or fragmented. However, they require strong validation against ground truth, clear documentation of assumptions, privacy controls, and explicit limits on commercial use. Synthetic data should support measurement, not obscure uncertainty (Paic, 2025, pp. 9, 13; Vanheuverzwyn & Rosanvallon, 2026, pp. 25-26).

Appendix D.

Sources and References

This report draws on CIMM's AI Innovation Showcase, related presentation materials and CIMM seminar discussions on marketing mix modeling, media quality and identity infrastructure. The report also considers public standards and market initiatives relevant to agentic advertising and AI-enabled video buying. These include IAB Tech Lab's Agentic Advertising and AI initiatives, the Ad Context Protocol, IAB guidance on AI-Powered Video Outcomes, WPP Media's Agentic Standards Initiative for Video Buying, and trade press reporting on premium video standards collaboration.

References

- 4A's & Nielsen. (2026). The impact of AI on measurement.
- Ad Context Protocol. (2026). Introduction to the Ad Context Protocol.
- AI4Media Consortium. (2024). AI for the media industry: A strategic research agenda from the AI4Media consortium. Updated edition, July 2024.
- Ali, A. M. (2025). The future of AI in the media. *International Journal of Humanities and Social Science*, 15, 403-413. <https://doi.org/10.30845/ijhss.v15p39>
- Andersen, S. H., & Signorini, A. (2025). The future is ultra: Why software will define the next era of measurement. ASI Copenhagen 2025.
- Catanoso, G. (2025). From theory to practice: Total content measurement. ASI Copenhagen 2025.
- CIMM. (2026). Identity Infrastructure 2.0: Innovation, transparency, and privacy-first architecture in the U.S. TV & CTV ecosystem. Coalition for Innovative Media Measurement.
- CIMM. (2026b). Quality Matters: Navigating quality in media buying and measurement. CIMM Research Seminar materials.
- CIMM. (2026c). Showcase for Innovations in AI. CIMM presentation and transcript materials.
- Databricks. (2025). The Data Intelligence Platform.
- Delechapt, L., & Rosanvallon, J. (2025). Cross-video ad-measurement. ASI Copenhagen 2025.
- IAB & BWG Global. (2026). State of Data 2026: The AI-powered measurement transformation: Implications for attribution, incrementality, and MMM.
- IAB, BWG Global, & Transparent Partners. (2025). State of Data 2025: The now, the near, and the next evolution of AI for media campaigns.
- IAB. (2026). AI-powered video outcomes. March 2026 guidelines.
- IAB Tech Lab. (2026). Agentic advertising and AI standards initiative.
- Independent International Scientific Panel on AI. (2026). Preliminary report of the Independent International Scientific Panel on AI: Evidence-based assessment of opportunities, risks and impacts of artificial intelligence. United Nations.
- Ivie, G. (2025). Measurement quality and standards: MRC priorities for standards development. ASI Copenhagen 2025.
- Jain, S., & Bradford, A. (2025). Applied data science: Building clarity through AI. Kantar Media, ASI Copenhagen 2025.
- Maslej, N., Fattorini, L., Perrault, R., Gil, Y., Parli, V., Kariuki, N., Capstick, E., Reuel, A., Brynjolfsson, E., Etchemendy, J., Ligett, K., Lyons, T., Manyika, J., Niebles, J. C., Shoham, Y., Wald, R., Walsh, T., Hamrah, A., Santarlasci, L., Betts Lotufo, J., Rome, A., Shi, A., & Oak, S. (2025). The AI Index 2025 annual report. Stanford Institute for Human-Centered Artificial Intelligence.

cimm

Coalition for Innovative
Media Measurement

