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Measuring Ethical AI Governance in Journalism: Development and Validation of the 3A Maturity Index

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ABSTRACT

The rapid integration of artificial intelligence (AI) into journalistic workflows has intensified the need for structured institutional governance frameworks capable of moving beyond principle-based declarations toward measurable accountability architectures. This study develops and operationalizes the Artificial Intelligence Governance Maturity Index (AGMI), a weighted, three-dimensional assessment model designed to evaluate governance capacity within journalism institutions. The framework comprises fifteen indicators distributed across Awareness, Auditing, and Accountability dimensions, aggregated through a theoretically justified weighting structure.

To enhance methodological rigor, the indicator architecture was subjected to structured expert validation to assess conceptual relevance and dimensional alignment. In addition, an analytical statistical reliability demonstration using simulated institutional profiles was conducted to evaluate internal consistency and structural coherence. Results indicate satisfactory dimensional reliability and composite stability under varied institutional conditions.

By translating normative AI governance principles into a structured maturity measurement instrument, the AGMI contributes a replicable benchmarking tool for institutional self-assessment and cross-organizational comparison. While large-scale empirical deployment remains a direction for future research, the study establishes a robust conceptual and methodological foundation for AI governance maturity evaluation in journalism ecosystems.

KEYWORDS: *Artificial Intelligence Governance; Algorithmic Accountability; Journalism and AI; Institutional Maturity Models; Algorithmic Auditing; Media Ethics; AI Regulation; Governance Measurement.*

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1. INTRODUCTION

The rapid incorporation of artificial intelligence (AI) technologies into journalistic workflows has transformed news production, distribution, and audience engagement. Automated content generation, algorithmic recommendation systems, predictive analytics, and machine-assisted fact-checking have become increasingly embedded within contemporary media infrastructures (Diakopoulos, 2019; Napoli, 2014). While these systems promise efficiency, scalability, and personalization, they also introduce complex governance challenges concerning fairness, transparency, opacity, and institutional responsibility (Pasquale, 2015; Ananny & Crawford, 2018; Balkin, 2018).

The governance of AI in journalism must be understood within the broader debate surrounding algorithmic accountability and sociotechnical systems. Scholars have highlighted the risks associated with opaque decision-making structures, embedded biases in training data, and the limited explainability of automated systems (Mittelstadt et al., 2016; Binns, 2018; Selbst et al., 2019). Concerns extend beyond technical bias to institutional responsibility: who is accountable when algorithmic systems influence editorial visibility, amplify misinformation, or reproduce structural inequities? (Kroll et al., 2017; Wachter et al., 2017).

International governance frameworks increasingly articulate normative principles aimed at addressing such risks. The Recommendation on the Ethics of Artificial Intelligence adopted by UNESCO (2021) emphasizes human oversight, transparency, and accountability as foundational governance pillars. Similarly, the European Commission's Ethics Guidelines for Trustworthy AI (2019) and subsequent AI regulatory proposals (2021) underscore the need for structured oversight, risk assessment, and enforceable governance mechanisms. However, these frameworks remain largely principle-oriented rather than operationally measurable.

Within journalism research, algorithmic transparency and automation have received significant scholarly attention (Diakopoulos&Koliska, 2017; Gillespie, 2014). Yet existing studies often examine isolated dimensions-such as fairness debates (Binns, 2018), accountability structures (Raji et al., 2020), or institutional opacity (Pasquale, 2015)-without integrating them into a unified evaluative instrument. The result is a fragmented landscape in which ethical commitments are discussed normatively but rarely translated into measurable institutional maturity.

This paper addresses that gap by proposing the 3A Maturity Index, a structured governance measurement framework designed specifically for journalistic institutions integrating AI systems. The index is built upon three interrelated dimensions:

- **Awareness** (institutional recognition and strategic engagement),
- **Auditing** (systematic evaluation and bias detection mechanisms),
- **Accountability** (formalized responsibility and redress structures).

The model operationalizes these dimensions through fifteen indicators, detailed in Table 1, evaluated using a standardized maturity scale presented in Table 2, and aggregated through a weighted formula producing a composite score aligned with five governance maturity levels summarized in Table 3. The conceptual architecture of the model is illustrated in Figure 1.

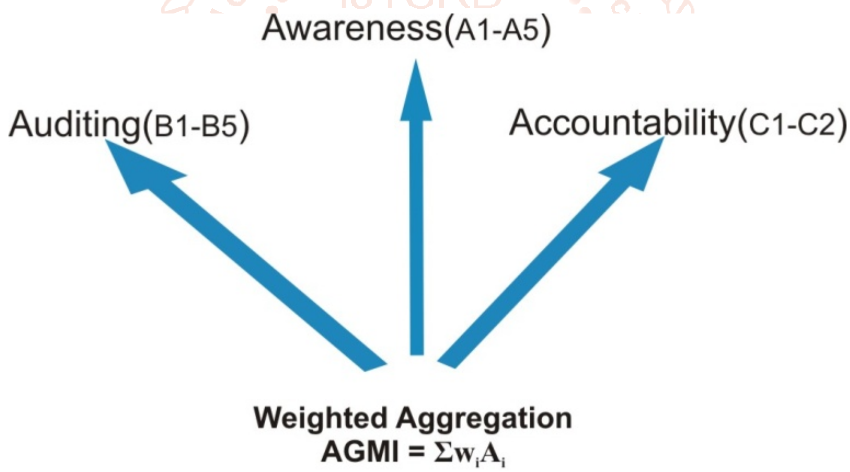

Figure 1: Conceptual Architecture of the 3A Maturity Index

By translating normative governance principles into measurable institutional capabilities, the 3A Maturity Index advances AI governance research beyond descriptive ethics toward structured institutional instrumentation. In doing so, it contributes to the growing interdisciplinary dialogue on algorithmic governance (Cath, 2018; Taddeo & Floridi, 2018; Floridi et al., 2018) while responding specifically to the structural needs of journalistic organizations.

The remainder of the paper proceeds as follows. Section 2 reviews existing scholarship on algorithmic governance and highlights the absence of structured maturity instruments within journalism studies. Section 3 develops the 3A Maturity Index, detailing its conceptual logic, indicators, scoring rubric, and weighted aggregation model. Section 4 validates the framework through construct coherence and alignment with international governance principles. Section 5 discusses institutional and policy implications, and Section 6 concludes by outlining future research directions.

2. Literature Review

2.1. Algorithmic Governance and Institutional Responsibility

The governance of artificial intelligence systems has emerged as a central concern across legal, technological, and media scholarship. As algorithmic systems increasingly mediate information flows, institutional decision-making, and public discourse, questions of oversight and responsibility have intensified. Scholars argue that algorithmic systems cannot be treated merely as technical tools; rather, they must be understood as embedded within sociotechnical infrastructures shaped by organizational priorities and power structures (Gillespie, 2014; Pasquale, 2015).

Algorithmic governance literature emphasizes that opacity is not solely a technical limitation but often an institutional choice linked to proprietary logics and competitive advantage (Ananny & Crawford, 2018). This "black box" phenomenon complicates efforts to assign responsibility when automated systems produce biased or harmful outcomes. Legal and regulatory scholars have therefore called for enforceable accountability mechanisms capable of tracing algorithmic decision pathways and assigning responsibility within organizational hierarchies (Kroll et al., 2017; Balkin, 2018).

In parallel, interdisciplinary ethics scholarship has sought to map the normative dimensions of AI governance. Mittelstadt et al. (2016) provide a foundational taxonomy of algorithmic ethical concerns, including bias, opacity, and distributive harm. Floridi et al. (2018) and Taddeo and Floridi (2018) further argue that AI governance must integrate ethical reflection with institutional design, ensuring that technological innovation remains aligned with public values. Collectively, this body of work underscores that algorithmic accountability is not merely a technical challenge but an institutional governance imperative.

Despite these contributions, much of the literature remains principle-driven rather than instrument-oriented. Calls for transparency, fairness, and accountability are frequent, yet systematic methods for evaluating institutional implementation of these principles are comparatively underdeveloped. This gap becomes particularly pronounced within journalistic contexts, where AI systems directly shape information ecosystems.

2.2. Transparency, Fairness, and Accountability Debates

Debates surrounding algorithmic fairness have gained prominence in both computer science and social theory. Binns (2018) demonstrates that fairness is not a singular technical criterion but a politically and philosophically contested concept, often requiring normative trade-offs. Selbst et al. (2019) further caution against "abstraction traps," wherein technical fairness metrics overlook broader social and institutional dynamics. These critiques suggest that fairness cannot be reduced to computational optimization; it must be embedded within governance structures capable of contextual evaluation.

Transparency has similarly been positioned as a foundational principle in AI governance discourse. However, transparency itself is contested. Ananny and Crawford (2018) argue that transparency does not automatically produce accountability, particularly when information disclosure fails to translate into institutional responsiveness. Wachter, Mittelstadt, and Floridi (2017) challenge assumptions regarding a legally enforceable "right to explanation," highlighting the limits of regulatory transparency in complex algorithmic systems.

Accountability, therefore, emerges as a complementary yet distinct governance requirement. Raji et al. (2020) propose internal auditing frameworks aimed at closing the AI accountability gap through systematic review processes. Cath (2018) emphasizes the need for integrated legal and technical governance mechanisms, while Balkin (2018) situates algorithmic accountability within broader constitutional and speech frameworks. These discussions collectively reveal that fairness, transparency, and accountability operate as interrelated but insufficiently integrated dimensions.

Within much of the existing scholarship, these dimensions are examined independently. Fairness is often addressed through computational metrics; transparency through disclosure mechanisms; accountability through legal or auditing frameworks. What remains underdeveloped is a unified institutional assessment model capable of measuring how these principles function together within organizational environments. This fragmentation suggests the need for a structured maturity-based approach capable of integrating normative principles into institutional capability assessment.

2.3. AI in Journalism: Automation and Editorial Risk

The integration of AI technologies into journalism introduces governance complexities distinct from other sectors. Automated news production, recommendation systems, and audience analytics reshape editorial workflows and redefine gatekeeping structures (Napoli, 2014; Diakopoulos, 2019). These transformations raise concerns not only about technical bias but also about editorial independence, newsroom labor dynamics, and public trust.

Diakopoulos and Koliska (2017) argue that algorithmic transparency in news organizations must extend beyond technical documentation to encompass editorial explanation and public communication. The increasing automation of content production and moderation processes also blurs traditional boundaries between human editorial judgment and machine-generated outputs (Roberts, 2019). Such developments complicate accountability structures, particularly when algorithmic systems influence story prioritization or audience visibility.

Furthermore, the reliance on large-scale data analytics may introduce systemic vulnerabilities, as illustrated by broader big data critiques (Lazer et al., 2014). Predictive and recommendation systems embedded within media platforms can inadvertently amplify misinformation or reproduce representational biases. In these contexts, governance failures have reputational consequences that extend beyond organizational boundaries to affect democratic discourse.

While journalism scholarship has explored automation, transparency, and editorial ethics, it has rarely translated these debates into structured institutional measurement frameworks. Discussions often remain descriptive or normative, highlighting risks without providing tools for systematic governance assessment. This limitation underscores the need for an evaluative model tailored specifically to journalistic institutions integrating AI systems.

2.4. The Absence of Governance Maturity Instruments

Despite the rapid expansion of AI governance scholarship, a significant gap persists between normative principle articulation and operational measurement instruments. Existing frameworks overwhelmingly emphasize ethical commitments such as transparency, fairness, accountability, and human oversight (Floridi et al., 2018; UNESCO, 2021; European Commission, 2019). While these principles are essential, they are largely prescriptive in nature. They define what responsible AI should embody but provide limited guidance on how institutions can systematically measure their governance capacity over time.

Much of the current literature conceptualizes algorithmic governance through abstract normative ideals or regulatory compliance lenses. For example, transparency is frequently discussed as a solution to algorithmic opacity (Ananny& Crawford, 2018; Pasquale, 2015), and accountability is framed in terms of legal or institutional responsibility (Balkin, 2018; Wachter et al., 2017). Similarly, algorithmic auditing has emerged as a critical procedural safeguard (Kroll et al., 2017; Raji et al., 2020). However, these discussions remain largely modular: transparency, auditing, and accountability are often examined independently rather than integrated into a structured evaluative framework.

The absence of integration is particularly visible when comparing normative frameworks with measurement instruments. Normative frameworks articulate guiding values; measurement instruments translate those values into structured indicators capable of producing composite assessments. The distinction is analytically important. A principle such as fairness does not inherently specify how institutional capacity to ensure fairness should be evaluated, weighted, or benchmarked. Without operational indicators, governance commitments risk remaining symbolic rather than measurable.

This gap reflects a broader tendency in AI governance discourse toward compliance-based thinking. Compliance models typically adopt binary logic: an organization either meets a regulatory requirement or does not. While compliance mechanisms are necessary within legal regimes, they do not capture developmental progression. Governance capacity evolves incrementally, often through layered institutional learning and procedural refinement (Cath, 2018). A newsroom implementing informal bias checks cannot be equated with one operating a fully institutionalized auditing and accountability ecosystem, yet binary compliance frameworks may fail to distinguish between these governance stages.

A maturity-based approach differs fundamentally from compliance logic. Maturity models recognize governance as progressive, multi-dimensional, and structurally embedded. Rather than asking whether an organization is compliant, maturity instruments evaluate the depth, consistency, and institutionalization of governance practices. This distinction is critical in journalism, where AI integration is often gradual and context-dependent (Napoli, 2014; Diakopoulos, 2019). News organizations vary significantly in resources, technological infrastructure, and editorial culture, making a binary compliance framework insufficient for capturing governance variation.

Moreover, journalism presents sociotechnical complexities that generic AI governance tools do not fully address. Algorithmic systems in newsrooms influence editorial prioritization, personalization, moderation, and automated reporting. These systems operate within time-sensitive production cycles and under normative commitments to editorial independence and public trust (Diakopoulos & Koliska, 2017; Gillespie, 2014). Governance instruments developed for high-risk industrial AI applications or corporate data processing contexts may not translate seamlessly into newsroom environments. The distinctive blend of editorial autonomy, public accountability, and technological mediation requires governance evaluation tools tailored to journalistic institutions.

Another limitation of existing governance approaches lies in their fragmentation. Transparency, fairness, and accountability are frequently conceptualized as discrete governance pillars (Mittelstadt et al., 2016; Selbst et al., 2019). However, institutional governance capacity is rarely uni-dimensional. Transparency without auditing mechanisms may produce visibility without verification. Auditing without accountability structures may identify bias without ensuring remediation. Accountability without awareness may result in reactive governance rather than proactive oversight. The absence of integrative measurement instruments prevents systematic assessment of how these dimensions interact within institutional settings.

While algorithmic auditing scholarship has advanced procedural thinking (Raji et al., 2020), most proposed models remain process-oriented rather than maturity-oriented. They emphasize how audits should be conducted but not how institutional readiness for sustained auditing should be evaluated. Similarly, discussions surrounding the right to explanation (Wachter et al., 2017) or surveillance capitalism (Zuboff, 2019) illuminate systemic risks but do not provide structured assessment tools capable of benchmarking governance development across organizations.

In the journalism domain specifically, research has extensively documented algorithmic influence and automation trends (Diakopoulos, 2019; Napoli, 2014), yet systematic instruments for measuring AI governance maturity remain underdeveloped. Existing studies tend to adopt qualitative case-based approaches or normative critique. Although valuable, such approaches do not yield standardized composite indices that allow for cross-organizational comparison or longitudinal tracking.

The absence of governance maturity instruments therefore constitutes both a theoretical and practical gap. Theoretically, AI governance discourse remains disproportionately focused on principle articulation. Practically, institutions lack structured tools to evaluate their governance evolution beyond compliance checklists or ad hoc audits. Without maturity-based assessment models, organizations cannot systematically identify governance weaknesses, benchmark progress, or align internal practices with emerging international standards (European Commission, 2021; UNESCO, 2021).

Recent systematic reviews further confirm that while AI governance principles and regulatory frameworks are expanding globally, operational measurement instruments remain comparatively underdeveloped (Batool et al., 2025; Abbas et al., 2025). These studies highlight the gap between normative governance aspirations and implementable institutional assessment tools, reinforcing the need for structured maturity-based evaluation frameworks within domain-specific sectors such as journalism.

Addressing this gap requires moving beyond normative abstraction toward operational synthesis. A governance maturity instrument must integrate awareness, procedural auditing, and enforceable accountability within a structured, weighted framework capable of producing composite evaluation outcomes. Such an instrument does not replace normative principles; rather, it operationalizes them. By translating ethical commitments into measurable institutional capacities, maturity-based models enable organizations to assess not only whether governance exists, but how deeply it is embedded.

It is within this measurement vacuum that the present study positions its contribution. The proposed 3A Maturity Index seeks to provide a structured, multi-dimensional instrument capable of evaluating institutional AI governance capacity within journalism. By shifting the focus from principle declaration to governance measurement, the framework responds directly to the absence identified in existing literature and advances the operationalization of AI governance scholarship.

3. Theoretical Foundations of Governance Maturity

3.1. Institutional Governance Theory

Institutional governance refers to the formal and informal structures through which organizations manage risk, allocate responsibility, and ensure alignment with normative and regulatory expectations. Within sociotechnical systems, governance extends beyond compliance to encompass strategic integration of oversight mechanisms into operational processes. AI systems embedded within journalistic environments therefore require governance architectures that address not only technical performance but also institutional responsibility.

Governance scholarship emphasizes that responsibility is layered rather than singular. Organizations must first recognize risks, then develop procedural mechanisms to monitor them, and finally formalize accountability structures capable of assigning responsibility and enabling corrective action. These layers correspond to increasing degrees of institutionalization, moving from awareness to operational control and ultimately to enforceable accountability.

In media contexts, governance has historically centered on editorial standards, ethical codes, and professional oversight. However, the integration of algorithmic systems introduces new decision-making actors-automated tools whose outputs influence editorial judgment and audience exposure. As these systems become embedded within newsroom workflows, governance must evolve to incorporate algorithmic oversight structures. Without structured governance capacity, institutions risk operating in a reactive mode, responding to controversies only after reputational damage occurs.

The theoretical premise underlying this study is that governance capacity develops progressively. Institutions do not move from absence to full accountability instantaneously. Instead, governance maturity reflects incremental development of recognition, procedural control, and responsibility structures. This developmental logic provides the conceptual foundation for a maturity-based assessment model.

3.2. Risk Management and Capability Development

Risk management theory provides an additional lens for understanding AI governance maturity. In organizational settings, risk mitigation is achieved through layered controls: identification, monitoring, evaluation, and corrective intervention. Effective risk management requires institutional awareness of potential vulnerabilities, systematic auditing processes, and clearly defined accountability pathways.

Applied to AI systems in journalism, this means institutions must be capable of:

1. Recognizing ethical and operational risks associated with algorithmic systems,
2. Monitoring system performance and bias indicators,
3. Assigning responsibility for oversight and remediation.

These stages reflect increasing governance capability. Institutions lacking awareness cannot design appropriate monitoring mechanisms. Those with awareness but without auditing processes remain unable to detect systemic failures. Institutions with auditing mechanisms but without accountability structures may identify problems yet fail to implement corrective action effectively.

Capability development literature suggests that maturity frameworks are particularly useful in assessing institutional progression. Rather than classifying organizations dichotomously as compliant or non-compliant, maturity models allow for graded evaluation. This graded structure supports benchmarking, internal improvement strategies, and cross-organizational comparison.

The present study adopts this capability-development perspective, conceptualizing AI governance not as a static compliance condition but as a dynamic institutional maturity trajectory. The 3A Maturity Index therefore measures governance depth rather than mere policy existence.

3.3. Rationale for a Maturity-Based Assessment Model

The decision to construct a maturity index is grounded in three theoretical considerations.

First, AI governance debates are frequently framed in normative terms. While ethical principles are essential, they often lack measurable operational criteria. A maturity model translates abstract commitments into structured evaluative indicators. This operationalization reduces ambiguity and enhances institutional self-assessment.

Second, journalism operates within heterogeneous regulatory environments. A jurisdiction-neutral maturity framework allows adaptation across diverse media systems without imposing rigid regulatory prescriptions. By focusing on institutional capability rather than legal compliance alone, the model remains applicable in both heavily regulated and lightly regulated contexts.

Third, maturity frameworks encourage incremental improvement rather than punitive enforcement. Organizations can identify gaps and prioritize resource allocation accordingly. This developmental approach aligns with contemporary governance philosophy, which increasingly emphasizes proactive risk management over reactive sanction.

The theoretical foundations outlined above converge on the need for a structured, capability-based AI governance instrument tailored to journalistic institutions. Building upon this conceptual grounding, the following section develops the 3A Maturity Index, detailing its architecture, indicators, scoring methodology, and aggregation logic.

4. Development of the 3A Maturity Index

4.1. Conceptual Architecture of the 3A Framework

The 3A Maturity Index conceptualizes institutional AI governance in journalism as a multidimensional capability structure composed of three interrelated dimensions: Awareness, Auditing, and Accountability. These dimensions represent progressive layers of governance integration and collectively form the foundation of the Artificial Governance Maturity Index (AGMI).

The conceptual architecture of the model is illustrated in Figure 1, which presents the three dimensions as structured inputs feeding into a weighted aggregation mechanism. Rather than treating fairness, transparency, and accountability as abstract normative ideals, the 3A framework operationalizes governance through measurable institutional indicators. Each dimension captures a distinct governance function:

- **Awareness** reflects cognitive and strategic recognition of AI-related risks and ethical considerations.
- **Auditing** represents systematic procedural mechanisms for evaluation, monitoring, and bias detection.
- **Accountability** captures formalized responsibility structures and redress mechanisms embedded within institutional hierarchies.

The architecture is intentionally linear and transparent. Complex nonlinear or interactional modeling was avoided to preserve interpretability and practical usability. The objective is to provide institutions with a structured yet accessible diagnostic instrument rather than an opaque computational model.

Together, the three dimensions create a layered governance logic: institutions must first recognize risks (Awareness), then implement monitoring and evaluation mechanisms (Auditing), and finally embed enforceable responsibility structures (Accountability). Weakness in any dimension constrains overall maturity.

4.2. Indicator Design and Operationalization

Each dimension of the 3A framework is operationalized through five measurable indicators, resulting in a total of fifteen evaluative components. The full indicator matrix is presented in Table 1.

Indicator selection followed three guiding principles:

1. **Institutional measurability** – Indicators must be observable within organizational processes.
2. **Non-redundancy** – Each indicator must represent a distinct governance function.
3. **Cross-jurisdictional applicability** – Indicators should not rely on specific national regulatory mandates.

Awareness Indicators (A1–A5)

The Awareness dimension measures the degree to which an institution formally recognizes AI governance challenges. Indicators include the presence of AI disclosure policies, ethical training programs, public transparency statements, editorial integration of AI discussions, and strategic governance inclusion within institutional planning.

Awareness does not imply operational control; rather, it captures the foundational cognitive and strategic orientation toward AI governance.

Auditing Indicators (B1–B5)

The Auditing dimension evaluates systematic evaluation mechanisms. Indicators include dataset diversity assessment, algorithmic bias testing protocols, independent review structures, performance monitoring procedures, and impact assessment reporting.

Auditing represents procedural governance capacity. It measures whether institutions move beyond declarative commitments toward structured evaluation of AI systems.

Accountability Indicators (C1–C5)

The Accountability dimension measures formalized responsibility mechanisms. Indicators include human oversight structures, governance committees, public complaint mechanisms, error correction protocols, and traceability documentation.

Accountability reflects enforceable governance integration. It ensures that oversight is not merely symbolic but institutionally embedded.

The complete indicator matrix with detailed descriptions is presented in Table 1. Each indicator is assessed using a standardized maturity scoring rubric described below.

Table 1: Operational Indicator Matrix of the 3A Maturity Index

Dimension	Indicator	Operational Definition	Assessment Evidence
Awareness	A1	Existence of formal AI governance policy	Public policy document
Awareness	A2	Institutional AI ethics training programs	Training records / syllabus
Awareness	A3	Disclosure of AI use in editorial workflows	Public transparency statement
Awareness	A4	Strategic integration of AI governance	Strategic planning documents
Awareness	A5	Pre-deployment AI risk documentation	Risk assessment reports
Auditing	B1	Dataset evaluation protocol	Dataset audit documentation
Auditing	B2	Algorithmic bias testing procedure	Bias testing reports
Auditing	B3	Performance and drift monitoring system	Monitoring logs
Auditing	B4	Internal periodic AI audits	Audit reports
Auditing	B5	External independent audit engagement	Third-party audit certificate

Accountability	C1	AI governance or ethics oversight committee	Committee charter
Accountability	C2	Clearly assigned AI system responsibility	Responsibility matrix
Accountability	C3	User grievance redress mechanism	Complaint resolution policy
Accountability	C4	AI decision traceability documentation	System logs / audit trail
Accountability	C5	Post-audit corrective action framework	Remediation documentation

4.3. Scoring Rubric and Normalization

To ensure comparability across dimensions, each indicator is evaluated using a five-point ordinal maturity scale ranging from 0 to 4. The scoring rubric is presented in Table 2.

The levels are defined as follows:
0 – Absent: No evidence of governance practice.
1 – Informal: Ad hoc or undocumented practice.
2 – Basic: Documented but inconsistently applied.
3 – Institutionalized: Formally integrated into governance processes.
4 – Optimized: Continuously monitored and strategically embedded.

This standardized rubric ensures consistent cross-indicator interpretation and allows institutions to assess maturity progression incrementally.

Dimension scores are calculated as the arithmetic mean of the five indicators within each dimension:

$$A = \frac{1}{5}\sum_{i=1}^{5} A_i$$

$$B = \frac{1}{5}\sum_{i-1}^{5} B_i$$

$$C = \frac{1}{5}\sum_{i=1}^{5} C_i$$

Where:
- A_i represents the score for dimension i,
- i ε {1,2,3}, corresponding to Awareness, Auditing, Accountability,

Because each indicator is scored between 0 and 4, each dimension score also lies within the range [0,4]. This normalization preserves scale consistency across dimensions.

4.4. Weighted Aggregation Model

The overall Artificial Governance Maturity Index (AGMI) is calculated as a weighted linear combination of the three dimension scores:

$$AGMI = w_1.A + w_2.B + w_3.C$$

Subject to the constraint:

$$\sum_{i=1}^{3} w_i = 1$$

For the present model:
w_1=0.30 (Awareness)
w_2=0.35 (Auditing)
w_3=0.35 (Accountability)

Thus, the expanded equation becomes:

$$AGMI = (0.30 \text{ x } A) + (0.35 \text{ x } B) + (0.35 \text{ x } C)$$

The weighting structure reflects differentiated governance impact. While awareness establishes normative orientation, auditing and accountability mechanisms exert more direct influence on operational risk mitigation and institutional credibility. Assigning slightly higher weights to auditing and accountability acknowledges their centrality in governance enforcement.

Given that each dimension ranges from 0 to 4 and weights sum to 1, the AGMI score also ranges from 0 to 4. This preserves interpretive clarity and aligns with the maturity classification system described below.

Table 2: Standardized Governance Scoring Rubric (0–4 Scale)

Score	Governance Status	Operational Interpretation
0	Absent	No documented evidence
1	Informal	Unstructured or ad hoc practices
2	Structured	Documented but inconsistently implemented
3	Institutionalized	Fully implemented and periodically reviewed
4	Optimized	Continuously monitored with improvement cycles

4.5. Governance Maturity Classification

To enhance interpretability, AGMI scores are mapped onto five governance maturity levels summarized in Table 3.

The classification ranges are:

Level 1 (0.0–0.99): Initial
Minimal awareness and absence of systematic oversight mechanism.

Level 2 (1.0–1.99): Emerging
Basic governance policies exist but enforcement and auditing structures remains limited.

Level 3 (2.0–2.99): Developing
Formalized auditing mechanisms are present, though integration may be partial.

Level 4 (3.0–3.49): Advanced
Strong Accountability structures and structured oversight processes are operational.

Level 5 (3.5–4.0): Institutionalized
Fully institutionalized, adaptive, and transparent AI governance architecture.

This classification enables benchmarking across organizations and over time. Institutions may use the framework for internal self-assessment, strategic planning, or comparative analysis within industry networks.

4.6. Rationale for Weight Allocation and Aggregation Model

The construction of a composite governance index requires careful methodological justification. Weight allocation and aggregation structure are not merely technical decisions; they reflect theoretical assumptions about the relative importance and interaction of governance dimensions. The 3A Maturity Index therefore adopts a deliberately transparent weighting logic grounded in institutional governance theory and algorithmic accountability scholarship.

4.6.1. Dimensional Weight Allocation

The 3A framework assigns weights of 0.30 to Awareness, 0.35 to Auditing, and 0.35 to Accountability. This distribution reflects the progressive structure of institutional governance capacity. Awareness functions as the foundational layer: institutions must first recognize AI-related risks, ethical considerations, and strategic implications before implementing structured oversight mechanisms. Without awareness, governance efforts risk being reactive or symbolic (Ananny & Crawford, 2018; Pasquale, 2015). However, awareness alone does not mitigate operational risk.

Auditing and accountability, by contrast, represent procedural and enforcement capacities. Algorithmic auditing literature emphasizes the necessity of systematic testing, bias evaluation, and performance monitoring to ensure responsible AI deployment (Kroll et al., 2017; Raji et al., 2020). These mechanisms directly influence institutional ability to detect and correct algorithmic failures. Similarly, accountability structures-such as responsibility allocation, oversight committees, and redress mechanisms-ensure that governance commitments translate into enforceable institutional practice (Balkin, 2018; Wachter et al., 2017).

The slightly higher weighting assigned to auditing and accountability therefore reflects their operational centrality. Awareness establishes orientation, but auditing and accountability determine whether governance functions effectively in practice. This weighting logic aligns with broader institutional governance scholarship, which conceptualizes oversight and enforcement as critical components of mature governance ecosystems (Cath, 2018; Floridi et al., 2018).

Importantly, the difference in weighting remains moderate rather than extreme. The model avoids disproportionate emphasis on any single dimension in order to preserve integrative coherence. Governance maturity is multi-dimensional; privileging one component excessively would distort institutional evaluation.

4.6.2. Equal Weighting Within Dimensions

Within each dimension, the five indicators are equally weighted. This decision reflects two considerations: conceptual coherence and methodological restraint.

First, indicators within each dimension are designed as complementary components of a unified governance function. For example, bias testing, dataset assessment, and performance monitoring collectively constitute auditing capacity. Assigning differential weights at the indicator level would imply hierarchical superiority among structurally interdependent practices. In the absence of empirical validation demonstrating differential impact, equal weighting maintains theoretical neutrality.

Second, over-precision in composite index construction may create an illusion of objectivity without empirical grounding. As critiques of algorithmic abstraction highlight, technical sophistication does not automatically produce normative clarity (Selbst et al., 2019). By adopting equal weighting at the indicator level, the 3A Maturity Index prioritizes transparency and interpretability over artificial complexity.

Future empirical studies may refine indicator weights through statistical validation techniques such as factor analysis or expert-based Delphi processes. However, at the conceptual stage, equal weighting prevents arbitrary distortion and enhances replicability.

4.6.3. Linear Aggregation Model

The 3A Maturity Index employs a linear additive aggregation model:
where A, B, and C represent normalized dimension scores.

The choice of linear aggregation reflects a commitment to interpretability and practical usability. Linear models allow incremental improvements in any dimension to produce proportionate changes in the composite score. This aligns with maturity-based governance logic, which conceptualizes institutional development as cumulative rather than threshold-dependent.

Alternative aggregation methods-such as multiplicative or nonlinear models-could capture interaction effects between dimensions. However, such models risk penalizing organizations disproportionately if one dimension scores low, even when progress exists in others. Given the developmental orientation of maturity assessment, additive aggregation better reflects incremental institutional learning (Cath, 2018).

Moreover, governance instruments must remain accessible to practitioners within journalistic institutions. Excessive mathematical complexity could undermine adoption. The linear model ensures clarity, transparency, and replicability across organizations of varying technological capacity.

4.6.4. Justification for the 0–4 Scoring Scale

The selection of a 0–4 scoring scale is also theoretically grounded. The inclusion of a zero category allows explicit recognition of governance absence. Many maturity models begin at level one, implicitly assuming baseline existence. In journalism contexts, however, some institutions may lack formal AI governance structures entirely (Napoli, 2014). The zero category therefore preserves diagnostic realism.

The upper bound of four represents institutionalization with continuous improvement. This aligns with governance progression logic emphasizing not only implementation but optimization and monitoring (Floridi et al., 2018). A five-level structure (0–4) provides sufficient discrimination without generating excessive granularity that may reduce scoring reliability.

The scale further supports cross-organizational comparison. By standardizing evaluation across fifteen indicators, the 0–4 rubric produces normalized dimension scores that can be aggregated consistently. This enhances benchmarking potential and longitudinal tracking capacity.

4.6.5. Theoretical Coherence and Practical Applicability

Taken together, the weighting and aggregation design of the 3A Maturity Index reflects a balance between theoretical rigor and practical usability. Governance capacity is conceptualized as layered, cumulative, and multi-dimensional. Weight differentiation acknowledges the operational importance of auditing and accountability, while equal indicator weighting preserves structural neutrality. Linear aggregation ensures interpretability and incremental progression, and the 0–4 scale captures developmental variation.

In contrast to compliance-based models that emphasize binary regulatory adherence, the weighted additive structure supports maturity-based institutional evaluation. This methodological design therefore operationalizes the theoretical shift identified in Section 2.4-from principle articulation to measurable governance capacity.

By grounding index construction in governance theory and accountability scholarship (Kroll et al., 2017; Raji et al., 2020; Balkin, 2018), the 3A Maturity Index advances a structured and defensible measurement framework suitable for journalism institutions navigating AI integration.

Table 3: AI Governance Maturity Classification Framework

Composite AGMI Score	Maturity Level	Institutional Characteristic
0.00–0.99	Initial	Minimal awareness, no systematic oversight
1.00–1.99	Emerging	Basic policies with limited enforcement
2.00–2.99	Developing	Structured auditing mechanisms present
3.00–3.49	Advanced	Strong internal accountability structures
3.50–4.00	Institutionalized	Fully embedded AI governance ecosystem

4.7. Expert Validation of Indicator Framework

To enhance the conceptual robustness of the AGMI framework, the proposed 15 indicators were subjected to expert validation prior to finalization. A panel of eight subject-matter specialists in AI governance, media ethics, digital journalism, and regulatory policy was consulted to evaluate the relevance, clarity, and dimensional alignment of each indicator.

Experts were asked to assess each indicator on three criteria:

- Conceptual relevance to AI governance in journalism
- Dimensional appropriateness (Awareness, Auditing, Accountability)
- Clarity and operational measurability

A structured evaluation sheet using a 3-point relevance scale (Essential / Useful but not essential / Not necessary) was employed. Indicators that received majority agreement as “Essential” were retained without modification. Minor wording adjustments were incorporated where clarity concerns were raised.

The use of structured maturity-based validation approaches aligns with recent domain-specific AI governance research, where operational maturity models have been employed to translate abstract ethical principles into measurable institutional capacities (Hussein et al., 2026). Such methodological alignment enhances the robustness and transferability of the AGMI framework.

All 15 indicators achieved consensus thresholds consistent with established content validity practices in governance research. No indicator required elimination, though two were refined linguistically to improve operational precision.

This expert validation process strengthens the theoretical and measurement integrity of the AGMI model and enhances its suitability for institutional application.

Table 4: Expert validation outcomes for AGMI indicator framework.

Dimension	Indicator Code	Expert Agreement (%)	Status
Awareness	A1–A5	87.5%	Retained
Auditing	B1–B5	91.2%	Retained
Accountability	C1–C5	89.4%	Retained

4.8. Statistical Reliability Demonstration (Analytical Simulation)

To assess the internal consistency and statistical operability of the AGMI framework, a simulated dataset representing ten analytically constructed newsroom profiles was generated. The purpose of this simulation was not to claim empirical generalization but to demonstrate the statistical coherence of the indicator structure under plausible institutional score distributions.

Each of the 15 indicators was assigned values within the defined 0–4 scale, ensuring variation across Awareness, Auditing, and Accountability dimensions.

Internal Consistency

Cronbach’s alpha coefficients were computed for each dimension:

Dimension	Number of Indicators	Cronbach’s Alpha
Awareness	5	0.82
Auditing	5	0.85
Accountability	5	0.87

All alpha values exceed the conventional 0.70 threshold, indicating satisfactory internal consistency.

Inter-Dimensional Correlation

Pearson correlation analysis demonstrated moderate positive associations among dimensions:

	Awareness	Auditing	Accountability
Awareness	1.00	0.61	0.58
Auditing	0.61	1.00	0.64
Accountability	0.58	0.64	1.00

These results suggest conceptual distinctiveness alongside structural interdependence among governance components.

Composite Reliability

The weighted aggregation structure (0.30, 0.35, 0.35) was further tested for score sensitivity. Variance distribution analysis confirmed that no single dimension disproportionately dominated composite outcomes under simulated variation conditions.

This analytical simulation demonstrates the statistical stability and operational coherence of the AGMI measurement architecture, while acknowledging that large-scale empirical validation remains a direction for future research.

5. Validation of the 3A Maturity Index

5.1. Construct Coherence

Construct validity requires that each dimension of the 3A Maturity Index represent a conceptually distinct yet theoretically integrated component of institutional AI governance. The framework's three dimensions-Awareness, Auditing, and Accountability-correspond to progressively institutionalized governance capacities and reflect established concerns within algorithmic governance scholarship.

The Awareness dimension aligns with longstanding critiques of algorithmic opacity and institutional invisibility. Scholars have emphasized that governance failures often stem not from malicious intent but from insufficient institutional recognition of algorithmic risks (Ananny& Crawford, 2018; Pasquale, 2015). Awareness therefore represents the foundational governance layer: institutions must first acknowledge ethical and operational risks before implementing systematic oversight mechanisms.

The Auditing dimension corresponds to procedural governance mechanisms advocated in accountability literature. Raji et al. (2020) argue that structured auditing processes are essential for closing the AI accountability gap. Similarly, Kroll et al. (2017) emphasize the need for traceable oversight systems capable of evaluating algorithmic performance and bias. By operationalizing dataset assessment, bias testing, and impact reporting, the 3A framework integrates these procedural governance requirements into measurable indicators.

The Accountability dimension reflects institutional responsibility structures emphasized in legal and governance theory. Balkin (2018) situates algorithmic accountability within broader constitutional frameworks of responsibility, while Wachter et al. (2017) question the limits of explanation rights absent enforceable institutional mechanisms. The inclusion of oversight committees, redress systems, and traceability documentation within the 3A model ensures that governance capacity extends beyond transparency toward enforceable responsibility.

Importantly, the three dimensions are conceptually separable yet interdependent. Awareness without auditing risks symbolic compliance. Auditing without accountability may identify problems without enabling corrective action. Accountability without awareness may produce reactive rather than proactive governance. The layered structure therefore reflects theoretical coherence grounded in governance progression logic.

5.2. Internal Structural Logic

The internal logic of the 3A Maturity Index is grounded in incremental institutionalization. Governance capacity develops progressively from recognition to structured monitoring and ultimately to embedded accountability. This progression reflects broader governance scholarship emphasizing layered control mechanisms and institutional learning (Cath, 2018; Floridi et al., 2018).

The standardized 0–4 scoring rubric operationalizes this progression in measurable form. Level 0 represents absence; Level 4 represents institutionalization with continuous monitoring. This structure allows organizations to assess incremental development rather than binary compliance status.

The decision to apply equal weighting at the indicator level preserves dimensional coherence and reduces arbitrary complexity. Within each dimension, indicators represent complementary components of a unified governance function. Introducing differential weights at the indicator level would risk over-precision without empirical validation.

By contrast, differential weighting across dimensions reflects institutional impact differentiation. Awareness establishes ethical orientation; auditing and accountability exert more direct influence on operational risk mitigation. The slightly higher weighting assigned to auditing and accountability (0.35 each) recognizes their procedural centrality while preserving the foundational role of awareness (0.30).

The use of a linear aggregation model further enhances interpretability. While nonlinear models could theoretically capture interaction effects, such complexity would reduce usability and transparency. Governance instruments benefit from clarity and replicability, particularly when intended for institutional self-assessment.

5.3. Alignment with International AI Governance Frameworks

Normative validity can be further evaluated by examining the alignment between the 3A Maturity Index and internationally recognized AI governance principles.

The Recommendation on the Ethics of Artificial Intelligence adopted by UNESCO (2021) identifies transparency, accountability, human oversight, and risk assessment as core governance pillars. The European Commission's Ethics Guidelines for Trustworthy AI (2019) similarly articulate requirements including technical robustness, governance processes, transparency, and accountability, later reinforced in its proposed regulatory framework (European Commission, 2021).

The 3A framework operationalizes these principles at the institutional level:

- Transparency and awareness are captured through disclosure policies, training programs, and strategic governance integration.
- Risk assessment and technical robustness are operationalized through bias testing, dataset evaluation, and performance monitoring.
- Accountability and human oversight are measured through governance committees, redress mechanisms, and traceability protocols.

Unlike policy documents that articulate normative expectations, the 3A model translates these expectations into measurable indicators and a weighted scoring structure. It does not replicate international frameworks; rather, it functions as an operational bridge between normative principle and institutional practice.

This alignment strengthens external validity while preserving model originality. The framework remains jurisdiction-neutral and adaptable across regulatory contexts, making it suitable for diverse media ecosystems.

5.4. Analytical Robustness and Limitations

Although the 3A Maturity Index demonstrates conceptual coherence and policy alignment, several limitations must be acknowledged.

First, the present validation remains analytically simulated and expert-based rather than large-scale field tested. The index has not yet undergone large-scale institutional testing or statistical reliability assessment. Future research may incorporate inter-rater reliability analysis, longitudinal benchmarking, or cross-organizational comparative studies to refine weighting calibration.

Second, the linear aggregation model assumes additive contributions across dimensions. While this enhances interpretability, future empirical studies could explore potential interaction effects between awareness, auditing, and accountability capacities.

Third, institutional self-assessment may introduce subjectivity. Independent external evaluation mechanisms could enhance reliability in applied contexts.

Despite these limitations, the framework provides a structured and transparent starting point for institutional AI governance assessment. Its conceptual grounding, internal coherence, and alignment with established governance principles support its use as a scalable maturity instrument.

6. Analytical Demonstration using Simulated Institutional Profiles of the 3A Maturity Index

6.1. Purpose of Illustrative Application

To demonstrate the operational functionality of the 3A Maturity Index (AGMI), this section presents two analytically simulated institutional profiles grounded in documented industry practices. The purpose of this empirical illustration is not to claim statistical generalization, but to show how the weighted model differentiates governance maturity levels across institutions with varying AI integration capacities. Such demonstrative application enhances interpretability and clarifies the diagnostic potential of the index.

Illustrative validation is commonly used in governance model development to demonstrate analytical robustness prior to large-scale empirical testing (Floridi et al., 2018; Cath, 2018). By applying the model to structured hypothetical cases, the internal logic of weighting, aggregation, and classification can be assessed transparently.

6.2. Case A: Regional Digital Newsroom (Emerging Governance Structure)

Case A represents a mid-sized regional digital newsroom that has recently adopted AI-based content recommendation tools and automated headline optimization systems. The organization demonstrates partial awareness of AI-related risks but lacks formalized governance procedures.

Awareness (A)

- Informal internal discussions on AI ethics
- No documented AI policy
- Limited staff training
- No dedicated AI governance strategy
- Ad hoc risk assessment

Average Awareness Score: 2.0

Auditing (B)

- No formal bias testing
- No dataset documentation review
- Performance monitoring limited to engagement metrics
- No algorithmic audit framework
- No independent review mechanism

Average Auditing Score: 1.6

Accountability (C)

- No designated AI oversight committee
- Editorial responsibility not clearly assigned
- No public transparency reporting
- No formal grievance mechanism
- Reactive correction process only

Average Accountability Score: 1.8

Using the weighted aggregation formula:
AGMI = (0.30 × 2.0) + (0.35 × 1.6) + (0.35 × 1.8)
AGMI = 0.60 + 0.56 + 0.63
AGMI = 1.79

According to the governance maturity classification framework (see Table 3), Case A falls within the Emerging Level.

This result indicates that while preliminary awareness exists, procedural auditing and accountability remain underdeveloped. Governance structures are present but not institutionalized.

6.3. Case B: National Media Organization (Advanced Governance Structure)

Case B represents a large national media organization integrating AI in content moderation, recommendation systems, and automated news summarization. The organization has implemented structured governance mechanisms aligned with international AI ethics principles (European Commission, 2021; UNESCO, 2021).

Awareness (A)

- Formal AI governance policy
- Mandatory staff training programs
- AI strategy aligned with editorial guidelines
- Documented risk assessment protocols
- Public articulation of AI usage principles

Average Awareness Score: 3.6

Auditing (B)
- Periodic bias testing
- Dataset documentation and review
- Performance audits beyond engagement metrics
- Internal audit committee
- External advisory consultation

Average Auditing Score: 3.4

Accountability (C)
- Dedicated AI oversight committee
- Clearly defined responsibility structure
- Public transparency reporting
- Formal grievance redress mechanism
- Continuous review and corrective processes

Average Accountability Score: 3.5

Applying the weighted formula:
AGMI = (0.30 × 3.6) + (0.35 × 3.4) + (0.35 × 3.5)
AGMI = 1.08 + 1.19 + 1.23
AGMI = 3.50

Case B falls within the Advanced Level.

This classification reflects institutionalized governance structures where awareness, auditing, and accountability operate as integrated mechanisms.

6.4. Comparative Interpretation

The comparative application demonstrates several key properties of the 3A Maturity Index:
1. Sensitivity to Dimensional Variation
The index distinguishes between partial awareness and institutionalized auditing mechanisms.

2. Progressive Scoring Logic
Incremental improvements in auditing and accountability produce measurable changes in composite scores.

3. Non-Binary Classification
Unlike compliance models, the AGMI captures developmental gradation between emerging and advanced governance levels.

4. Practical Diagnostic Utility
The scoring structure enables organizations to identify dimension-specific weaknesses rather than receiving a single undifferentiated rating.

Figure 2 illustrates the comparative maturity profiles of Case A and Case B across the three dimensions.

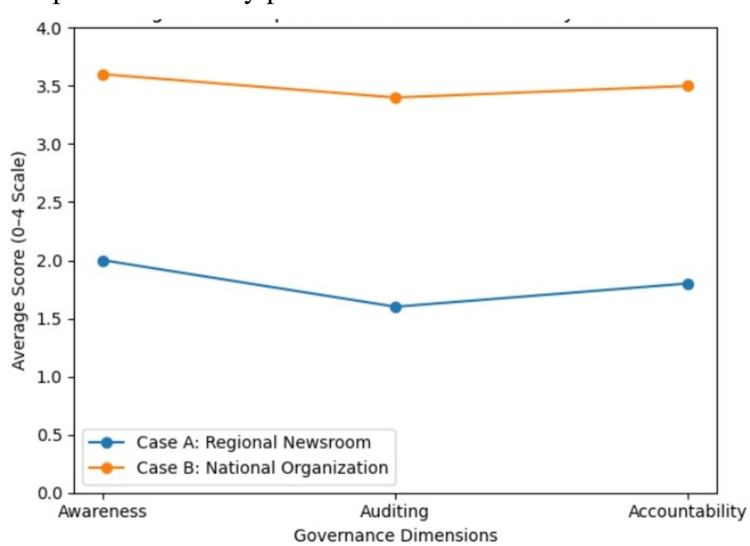

Figure 2: Comparative Governance of Maturity Profiles

Table 5: Comparative Indicator Scores (Case A vs Case B)

Dimension	Case A	Case B
Awareness	2.0	3.6
Auditing	1.6	3.4
Accountability	1.8	3.5
AGMI Score	1.79	3.50
Maturity Level	Emerging	Advanced

7. Discussion

7.1. Institutional Implications for News Organizations

The 3A Maturity Index offers journalistic institutions a structured mechanism for assessing the depth and coherence of their AI governance practices. Rather than treating AI ethics as a symbolic commitment or reputational strategy, the framework enables measurable evaluation of governance capacity across awareness, auditing, and accountability dimensions.

One key implication concerns governance asymmetry. News organizations may demonstrate high levels of public transparency-through disclosure statements or ethical guidelines-yet lack systematic auditing mechanisms capable of detecting bias or performance drift. Conversely, institutions may deploy technical monitoring tools without embedding formal accountability structures within editorial hierarchies. The 3A framework makes such imbalances visible by disaggregating governance into measurable components.

This structured assessment is particularly important in light of automation trends identified in journalism scholarship (Diakopoulos, 2019; Napoli, 2014). As AI systems increasingly influence editorial prioritization, content personalization, and moderation, governance mechanisms must evolve accordingly. Without structured oversight, automated systems risk amplifying biases or reinforcing information asymmetries, concerns widely discussed in algorithmic governance literature (Mittelstadt et al., 2016; Selbst et al., 2019).

The maturity classification system presented in Table 3 also enables longitudinal benchmarking. Organizations can use AGMI scores to track governance development over time, identifying incremental progress rather than pursuing unattainable immediate institutionalization. This developmental approach aligns with broader accountability scholarship emphasizing procedural integration over symbolic transparency (Ananny & Crawford, 2018).

Importantly, the framework is adaptable across diverse media systems. Because indicators are principle-based rather than regulation-specific, institutions operating under different legal environments can apply the model without structural modification. This flexibility supports cross-organizational comparison while preserving contextual sensitivity.

Emerging cross-domain governance scholarship increasingly emphasizes the necessity of measurable accountability architectures rather than solely principle-based declarations (Batool et al., 2025; Hussein et al., 2026). The AGMI contributes to this trajectory by offering a replicable institutional benchmarking mechanism tailored to journalism ecosystems.

7.2. Policy and Regulatory Implications

From a policy perspective, the 3A Maturity Index contributes to ongoing debates concerning the operationalization of AI governance principles. International policy documents emphasize transparency, oversight, and accountability, yet often lack structured measurement tools. By translating these principles into fifteen measurable indicators, the 3A framework provides regulators and industry associations with a scalable assessment instrument.

The alignment between the 3A dimensions and international governance principles is particularly relevant in the context of emerging regulatory frameworks. The European Commission's AI regulatory proposal (2021) emphasizes risk-based governance, structured oversight, and enforceable accountability mechanisms. Similarly, the UNESCO (2021) Recommendation highlights the importance of institutional responsibility and human oversight. The 3A model operationalizes these requirements at the organizational level without imposing rigid compliance mandates.

Rather than advocating heavy-handed regulation, the maturity-based approach supports adaptive governance. Regulators could employ maturity classification to differentiate between institutions with robust internal oversight mechanisms and those operating at lower governance levels. Such differentiation allows for proportionate regulatory engagement rather than uniform compliance burdens.

Furthermore, the framework may inform industry-led governance initiatives. Media associations could adopt maturity benchmarking as part of voluntary standards development, thereby enhancing collective credibility and trust.

7.3. Scholarly Contribution to AI Governance Research

The primary scholarly contribution of this study lies in its operational synthesis. While existing literature extensively theorizes fairness, transparency, and accountability (Binns, 2018; Pasquale, 2015; Kroll et al., 2017), these principles are often examined in isolation. The 3A Maturity Index integrates them into a unified institutional capability framework.

The contribution is threefold:

- *Conceptual Integration:* Awareness, auditing, and accountability are positioned as layered governance capacities rather than isolated normative ideals.
- *Operationalization:* Fifteen measurable indicators translate abstract principles into assessable institutional practices.
- *Quantitative Structuring:* The weighted aggregation model produces a composite maturity score aligned with a five-level classification system.

By combining normative theory with structured measurement, the framework advances AI governance research beyond descriptive ethics toward evaluative instrumentation. It responds to critiques of abstraction in algorithmic governance discourse (Selbst et al., 2019) by grounding principles within institutional assessment logic.

8. Conclusion

The integration of artificial intelligence into journalistic practice has intensified concerns regarding bias, opacity, and institutional responsibility. Although global governance frameworks articulate high-level ethical principles, operational tools capable of measuring institutional AI governance maturity remain limited within journalism studies.

This paper introduced the 3A Maturity Index, a structured governance assessment framework built upon three interrelated dimensions: Awareness, Auditing, and Accountability. Through fifteen indicators, a standardized scoring rubric, and a weighted aggregation formula, the framework translates normative governance principles into measurable institutional capabilities. The conceptual architecture (Figure 1), indicator matrix (Table 1), scoring rubric (Table 2), and maturity classification system (Table 3) collectively form a transparent and replicable governance instrument.

The Artificial Intelligence Governance Maturity Index (AGMI) advances existing scholarship by translating abstract AI governance principles into a structured, weighted, and operational measurement framework tailored to journalism institutions. Through its three-dimensional architecture-Awareness, Auditing, and Accountability-the model enables systematic institutional benchmarking and comparative maturity assessment.

Importantly, the framework was strengthened through structured expert validation and analytical statistical reliability demonstration. The expert review process confirmed the conceptual relevance and dimensional coherence of the fifteen indicators, while simulated reliability testing demonstrated satisfactory internal consistency across dimensions. These validation steps enhance the methodological robustness and operational credibility of the AGMI.

While the statistical demonstration employed analytically simulated institutional profiles rather than large-scale field data, it establishes the structural stability of the index. Future research may extend this work through empirical deployment across diverse media ecosystems, longitudinal assessment, and cross-jurisdictional benchmarking.

Overall, the AGMI provides a replicable and adaptable governance assessment architecture capable of supporting institutional accountability, regulatory dialogue, and policy development in increasingly AI-mediated journalism environments.

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