

The Impact of Algorithmic Bias and Cultural Representation in Artificial Intelligence Systems on the Performance of Digital Media Organizations in East Asia

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Abstract

The increasing adoption of artificial intelligence (AI) and data-driven decision-making has fundamentally transformed digital media organizations, particularly in the areas of automated content creation, news recommendation, audience targeting, content personalization, and information distribution. While these technologies offer significant opportunities to enhance organizational efficiency, audience engagement, innovation, and decision-making, they also introduce critical challenges related to algorithmic bias and cultural representation. These challenges are particularly significant in East Asia, where diverse cultural identities, languages, social values, and media environments interact with rapidly developing AI technologies. Algorithmic systems developed primarily from data and cultural contexts that do not adequately represent local populations may fail to reflect the cultural diversity and communication preferences of audiences in countries such as China, Japan, and South Korea. Such limitations may influence the visibility and diversity of media content, audience engagement, user trust, organizational decision-making, innovation, and the overall performance of digital media organizations.

Accordingly, this study investigates the impact of algorithmic bias and cultural representation in AI systems on the performance of digital media organizations in East Asia, with particular emphasis on China, Japan, and South Korea. The study examines how these factors may influence key dimensions of organizational performance, including audience engagement, user trust, content diversity, media pluralism, employee performance, innovation performance, and organizational decision-making. By integrating perspectives from artificial intelligence, algorithmic bias, cultural representation, media studies, and organizational performance, the study seeks to contribute to the emerging literature on responsible AI and provide practical implications for building more inclusive, trustworthy, and effective digital media organizations in East Asia.

Keywords: Artificial Intelligence, Algorithmic Bias, Cultural Representation, Digital Media Organizations, Organizational Performance

Introduction:

Organizations are increasingly adopting data analytics, big data technologies, and artificial intelligence (AI) to improve core business processes and support organizational decision-making (Chen et al., 2012; Mikalef et al., 2018).

According to the International Data Corporation (IDC), the Western European market for big data and analytics software reached approximately USD 14.6 billion in 2018 and was expected to grow at a compound annual growth rate of 8.2% over the following five years (Wells & Spinoni, 2019). Similarly, a 2018 survey of 200 U.S. financial institutions found that all participating organizations used some form of machine learning, while 91% of the largest banks relied on deep learning algorithms to support data-driven decision-making (PYMNTS, 2018).

Algorithmic systems are primarily used to: Automate decision-making processes; Support decision-makers by providing algorithmically generated information; Classify borrowers according to risk levels.; Predict the probability of loan default; Recommend decisions, such as approving or rejecting loans.

1.1. Algorithmic Bias

Despite the considerable value provided by AI and data analytics, algorithms operating as "black boxes" may create ethical risks at multiple levels within organizations and society (Martin, 2019; Someh et al., 2019). One of the most significant risks is that algorithms designed to improve the accuracy of organizational decisions may reproduce and even reinforce existing social biases (O'Neil, 2016).

Consequently, algorithmic systems used to automate or support decisions concerning individuals may generate discriminatory outcomes that violate principles of fairness and equality and negatively affect particular individuals or groups.

Algorithmic bias occurs when algorithmic outputs provide advantages or impose disadvantages on particular individuals or groups without objective justification for such unequal treatment.

Although computer scientists have developed various mathematical methods for detecting and mitigating algorithmic bias, Information Systems researchers have been relatively slower to investigate the behavioral, organizational, and social dimensions of this phenomenon, as well as its causes and consequences (Someh et al., 2019).

To address this research gap, the present study reviews the relevant academic literature and proposes a theoretical perspective explaining the relationships among algorithmic bias, perceived fairness, and behaviors associated with the use of intelligent systems.

AI has become one of the most influential technologies in digital media. AI algorithms determine which news stories users read, which videos appear on streaming platforms, and which advertisements are presented to them. These systems process enormous volumes of user data to maximize engagement and revenue.

However, AI algorithms are not inherently neutral. They reflect biases embedded in training data, assumptions made by developers, and the objectives for which algorithms are

optimized. As a result, AI systems may favor dominant cultural narratives while marginalizing minority voices or reinforcing stereotypes.

The issue is particularly important in East Asia, including China, Japan, South Korea, and North Korea, where digital media organizations operate in culturally diverse environments characterized by different languages, historical contexts, and social values. When AI systems fail to represent these cultures accurately, organizations may experience declining public trust, lower audience engagement, and reputational damage.

The work of (Kordzadeh & Ghasemaghahi, 2022) is particularly relevant because it conceptualizes algorithmic bias as a socio-technical phenomenon resulting from interactions among data, algorithm design, human behavior, and organizational factors. Their framework suggests that algorithmic bias affects users' perceptions of system fairness, which can subsequently influence behaviors such as acceptance of algorithmic recommendations, trust in intelligent systems, and organizational adoption of AI.

Accordingly, this literature provides a valuable theoretical foundation for examining algorithmic bias, algorithmic fairness, algorithmic accountability, and AI governance, particularly when comparing approaches to algorithmic regulation, transparency, and accountability across East Asian countries (Pessach & Shmueli, 2020).

2. Research Problem

Despite the rapid development and widespread adoption of AI and data analytics, algorithms may generate biased decisions that contribute to: Discrimination in employment; Unfairness in lending decisions; Bias in healthcare; Discrimination within criminal justice systems; and the widening of social and economic inequalities.

Many global AI models, particularly foundation models and large-scale language and vision models, are affected by imbalances in training data, the dominance of English-language digital content, and cultural values and contexts that do not represent all societies equally.

Previous academic research has highlighted that AI training datasets do not adequately represent global cultural diversity and that technologies developed in a limited number of countries may incorporate the cultural values and practices of those countries (Prabhakaran, Qadri, & Hutchinson, 2022).

A major concern is that many AI systems used by digital media organizations are trained primarily on datasets reflecting Western contexts. AI systems learn patterns and relationships from their training data. Therefore, when training data are culturally or linguistically imbalanced, models may become more capable of understanding and representing certain cultures and languages than others (Mohamed, Png, & Isaac, 2020).

(Prabhakaran, Qadri, & Hutchinson, 2022), in their position paper *Cultural Incongruencies in Artificial Intelligence*, argued that AI training data do not fairly represent global cultural diversity and that technologies developed in a limited number of countries may incorporate values and cultural practices associated with those countries. This problem becomes particularly significant when such systems are deployed in societies with different cultural values and contexts.

The study was also presented at the Cultures in AI/AI in Culture Workshop at NeurIPS 2022. It should be noted that this work is a conceptual position paper rather than an empirical comparative study of East Asian countries.

For example, if an AI model is asked to generate an image or description of a Japanese person, it might emphasize anime, samurai, or kimono, even when the intended representation is a contemporary Japanese citizen living in Tokyo and working for a technology company. The problem is not that information about samurai or anime is necessarily inaccurate; rather, the problem is that a limited aspect of Japanese culture may be presented as representative of Japanese culture as a whole.

Research by Qadri and colleagues on text-to-image models in South Asia has similarly shown that such systems can reproduce an "outsider's view" of non-Western cultures and reflect global cultural power imbalances in the representation of societies. Although this research focuses on South Asia rather than East Asia, it provides an important example of a mechanism that may also affect the representation of other Asian cultures.

2.1. Cultural Stereotypes

Cultural stereotypes occur when AI systems rely on simplified or repetitive representations of a particular culture instead of providing a diverse and contemporary representation.

For example, AI systems may associate:

Japan: Samurai, kimono, anime, technology, and robots.

China: The Great Wall, dragons, traditional clothing, and kung fu.

South Korea: K-pop, Korean dramas, cosmetics, and modern fashion.

Although these elements are genuinely associated with these cultures, the problem emerges when they become the dominant or exclusive representations of these societies while contemporary daily life and internal social and cultural diversity are overlooked.

In digital media, if organizations use automated systems to generate images, headlines, or recommendations, these systems may repeatedly reproduce cultural stereotypes, thereby becoming part of the process through which stereotypes are culturally reproduced.

2.2. Language Bias

Language bias occurs when some languages are more strongly represented in training data than others, resulting in better AI performance for languages with greater digital resources.

Many multilingual large language models remain English-oriented because of imbalances in training datasets. Expanding the number of supported languages does not automatically eliminate bias, as inequalities may persist or shift across languages and cultures.

For example, a news recommendation system trained predominantly on English-language content may understand the term "Artificial Intelligence Governance" more accurately than a culturally specific term in Japanese, Korean, or Chinese.

In digital media, this may result in: Poor translation of local terminology; Misinterpretation of cultural expressions; Loss of meaning during news translation; Poor classification of local content; Less accurate recommendations.

This issue is particularly important in East Asia because language is not merely a communication tool; it also carries cultural, historical, and social meanings.

2.3. Unequal Representation of Ethnic Groups

Unequal representation occurs when certain demographic or ethnic groups are underrepresented in AI training datasets.

This does not necessarily mean that an algorithm "dislikes" a particular group. Rather, the problem may arise because the data used to train the system do not reflect the actual distribution and diversity of the population (Cotter & Reisdorf, 2020).

In East Asia, this may affect: Image generation; Facial recognition; Content classification; News recommendation; Audience analysis.

Multilingual AI research also demonstrates that expanding the number of languages supported by a model does not automatically eliminate bias. Inequalities may continue to exist or change across different languages and cultural groups.

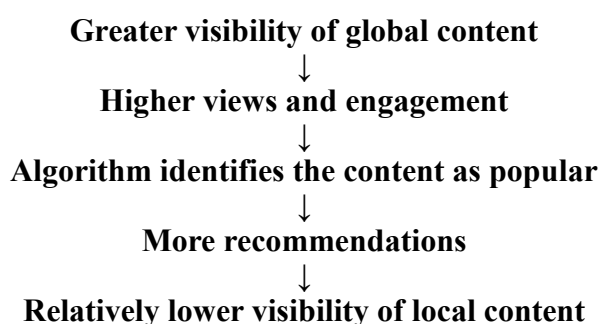
2.4. Reduced Visibility of Local Content

This issue is particularly important for digital media organizations.

Recommendation algorithms often rely on indicators such as: Views; Click-through rates; Engagement; Popularity; Watch time.

Consequently, they may promote content that already performs well while reducing the visibility of local or less popular content (Thurman et al., 2019).

This can create an algorithmic feedback loop:



Research on cultural recommendation systems has highlighted that recommendation algorithms increasingly regulate individuals' access to cultural content. Therefore, evaluating recommendation systems solely according to individual user satisfaction may overlook their broader impact on cultural diversity (Helberger, 2019).

In South Korea, (1) Park (2026), through focus group interviews (FGIs), examined users' experiences with AI-driven OTT platforms and found that recommendation algorithms may encourage repeated exposure to dominant content, limiting perceived content diversity and making non-mainstream content more difficult to access for some groups vulnerable to cultural exclusion.

2.5. Algorithmic Discrimination

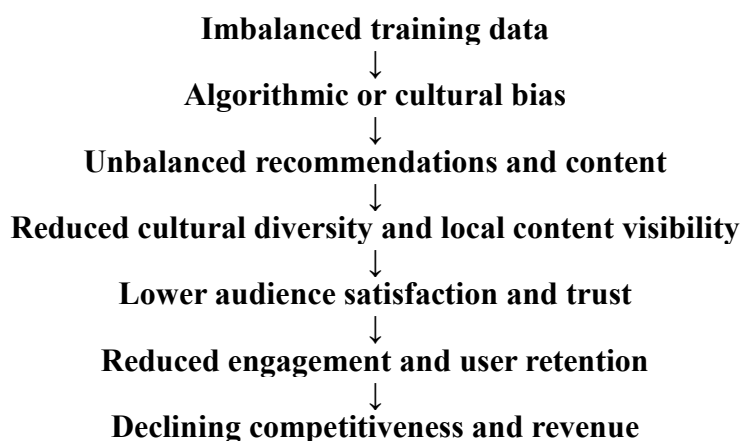
Algorithmic discrimination occurs when system decisions or outputs result in unfair or unequal treatment of particular groups because of data, model design, or optimization objectives.

For example, a digital media platform may use an algorithm to determine which news stories users see. If the algorithm learns that users interact more with celebrity news or global content, it may prioritize such content while reducing the visibility of: Local news; Minority-related news; Cultural issues; Content in less widely used languages.

Over time, this may create inequality in access to information. The problem becomes more serious when algorithms are opaque and neither users nor organizations can determine why particular content is promoted while other content is suppressed (Noble, 2018).

2.6. Impact on Digital Media Organizations

The relationship can be summarized as follows:



Thus, algorithmic bias is not merely a technical issue. Recommendation systems directly influence how audiences discover cultural and media content. Therefore, their evaluation should consider not only recommendation accuracy and individual user satisfaction but also cultural diversity and the public interest.

3. Research Objectives

This study aims to: Examine algorithmic bias in AI systems; Investigate cultural representation in digital media in East Asia; Analyze how AI bias affects organizational performance; Evaluate the ethical challenges associated with algorithmic systems; Provide recommendations and strategies for reducing algorithmic bias.

4. Literature Review

4.1. Artificial Intelligence in Digital Media

AI supports numerous digital media processes, including: Personalized recommendations; Automated journalism; Social media content moderation; Content creation; Advertising optimization; Audience analytics (Gillespie, 2014).

These technologies improve efficiency and reduce operational costs. However, they also increase dependence on opaque algorithms that influence and shape public discourse (Napoli, 2014).

4.2. Algorithmic Bias

Algorithmic bias refers to systematic and unfair discrimination produced by AI systems. Bias may originate from humans, data, algorithms, or the way systems are used.

Why Can Algorithmic Bias Be More Dangerous Than Human Bias?

Algorithmic bias can Operate at extremely high speed; Affect millions of decisions within a short period; Be difficult to detect because of algorithmic complexity; Give biased decisions an appearance of objectivity; Automatically reproduce historical patterns of discrimination; Common sources of algorithmic bias include (Zhou, Zhang, Nair, Singhal, Chen, & Sudjianto, 2021).

Dataset Bias: Training data may overrepresent certain populations while underrepresenting others.

Sampling Bias: Some demographic groups may not receive adequate representation in the datasets used to train AI systems.

Historical Bias: Existing patterns of historical discrimination may be incorporated into AI decision-making.

Labelling Bias: Human data annotators may unintentionally introduce subjective judgments into training data.

Optimization Bias: Algorithms may optimize engagement and participation rather than fairness and equity. These biases can affect recommendation quality and media content diversity.

Algorithmic bias is not merely a technical problem; it represents an extension of social biases within society. Algorithms learn from human-generated data, and when such data contain stereotypes, prejudices, or discriminatory practices, intelligent systems may reproduce and amplify them (Benjamin, 2019). Therefore, reducing algorithmic bias requires simultaneous attention to technical, social, and organizational dimensions.

4.3. Cultural Representation

Cultural representation refers to how AI systems represent: National identity; Gender; Race and ethnicity; Language; Traditions; Religion; Social values.

Weak cultural representation can reinforce stereotypes rather than accurately reflecting authentic cultural diversity.

5. AI and Digital Media in East Asia

East Asia represents one of the world's largest digital media markets.

China: Extensive AI adoption; Highly personalized recommendation systems; Strong government regulation.

Japan: Advanced robotics and AI integration; Strong interest in cultural preservation.

South Korea: Globally influential digital entertainment industry; Increasing use of AI in media production; Highly connected digital audiences.

Despite their technological leadership, these countries face similar concerns regarding algorithmic fairness, transparency, accountability, and cultural inclusivity.

6. Forms of Algorithmic Bias in East Asia

Algorithmic bias in East Asia does not take a single form. It is shaped by each country's social, cultural, political, and technological context.

In Japan and China, empirical evidence is particularly visible in employment and job recommendation systems, including gender bias resulting from demographic characteristics or indirect indicators used in matching and evaluation. In South Korea, transparency, fairness, and accountability are major challenges in algorithmic governance. In China, algorithmic governance is also closely connected to the regulatory and political environment. Research on North Korea remains highly limited because of the scarcity of reliable empirical data.

Language Bias

Many AI datasets remain dominated by English-language content, which may result in: Lower translation quality; Misinterpretation of local expressions; Lower recommendation accuracy.

Cultural Bias

AI systems may associate East Asian cultures with simplified stereotypes, such as: Traditional clothing.

Martial arts; Japanese anime; Historical imagery, rather than representing contemporary social realities.

Gender Bias

Women may be disproportionately represented in traditional occupations and roles, while leadership positions may continue to be associated disproportionately with men. Such representations may influence audience perceptions and attitudes.

Ethnic Bias

Minority populations may receive: Less visibility in digital content; Fewer recommendations; Less accurate AI-generated content.

Table 1. Potential and Empirically Documented Forms of Algorithmic Bias in East Asia

Country	Main Form of Bias	Area/Application	How Bias Appears	Example/Case	Scientific Source
Japan	Gender bias	AI-assisted recruitment and LLMs	Indirect indicators such as names or gender-related information may affect candidate evaluation	A 2026 study testing LLMs with Japanese <i>irekisho</i> resumes found gender bias favoring female candidates; removing names substantially reduced the effect	Hoffstedde et al. (2026)

Country	Main Form of Bias	Area/Application	How Bias Appears	Example/Case	Scientific Source
Japan	Cultural and linguistic bias	LLMs and generative AI	Global models may not equally reflect Japanese cultural and linguistic characteristics	Challenges arise when global models are transferred to Japanese language, labor markets, and cultural contexts	Hoffstedde et al. (2026)
China	Gender bias	Job recommendation systems	Job-matching algorithms may recommend different jobs to men and women with comparable professional profiles	An audit of major Chinese job platforms found differences in recommended jobs and job characteristics by gender	Zhang & Kuhn (2024/2025)
China	Data and social-behavior bias	Recommendation systems	Algorithms may reproduce patterns embedded in historical user behavior	Recommendation feedback loops may reinforce existing preferences and social patterns	(Shin, 2019)
China	Political/value-related bias	Digital platforms and algorithms	Regulatory and political rules may influence content availability and recommendation	Algorithmic governance raises questions regarding transparency, censorship, and platform autonomy	(Shin, 2019)
South Korea	Gender and social bias	Employment and digital services	Existing social biases may be transferred into data and algorithms	Algorithmic decision-making raises concerns about fairness and accountability	(Shin, 2019)
South Korea	Opacity bias	Online platforms and algorithms	Lack of transparency makes it difficult to identify or challenge algorithmic decisions	Users may not understand why specific content is recommended	(Shin, 2019)
North Korea	Political and ideological bias	Information systems and digital communication	Centralized political and media environments may influence information outputs	This remains a contextual hypothesis rather than empirically demonstrated bias in a specific algorithm	Methodological caution required

Country	Main Form of Bias	Area/Application	How Bias Appears	Example/Case	Scientific Source
North Korea	Digital access bias	Digital information and services	Unequal access to digital information creates unequal benefits from digital systems	Limited access to the open Internet makes North Korea fundamentally different from other East Asian countries	Analytical inference; not direct empirical evidence

The comparison suggests five major forms of algorithmic bias:

Gender bias, particularly evident in employment and job recommendation systems in Japan and China.

Data-driven bias, where algorithms learn and reproduce historical social inequalities.

Cultural and linguistic bias, particularly relevant when global AI models are applied to Asian cultural and linguistic contexts.

Transparency and accountability bias, resulting from the difficulty of understanding or challenging algorithmic decisions.

Political and ideological bias, which is particularly relevant to discussions of China's regulatory environment and may be considered analytically in the North Korean context, although direct empirical evidence remains insufficient.

The evidence therefore differs substantially across countries. Japan and China have stronger empirical evidence in employment-related applications, while South Korea has significant literature concerning algorithmic transparency, fairness, and accountability. Research concerning North Korea remains highly limited and should be presented cautiously as contextual analysis rather than established empirical evidence.

7. Impact of Algorithmic Bias on Organizational Performance

Algorithmic bias can affect multiple dimensions of organizational performance.

Audience Trust: Users may lose trust when AI systems repeatedly produce biased content, resulting in: Lower user loyalty; Reduced platform usage.

Audience Engagement: Recommendation systems that fail to reflect users' cultural preferences may reduce: Click-through rates; Viewing time; User retention.

Brand Reputation: Public criticism related to AI-driven discrimination can damage organizational reputation and increase ethical scrutiny from stakeholders.

Advertising Revenue: Lower engagement may lead to: Fewer advertising impressions; Lower conversion rates; Reduced advertising revenue.

Market Competitiveness: Organizations that fail to represent local cultures appropriately may lose competitive advantages to platforms that better adapt to local cultural contexts.

8. Cases

Case 1: Gender and Cultural Representation in Image Generation

Recent research analyzing image-generation models has identified recurring biases in the representation of East Asian women, including stereotypical appearances, gendered occupational roles, orientalist imagery, and limited aesthetic diversity.

Case 2: Recommendation Systems and Cultural Homogenization

Audits of recommendation systems used by major East Asian e-commerce platforms suggest that algorithms may reinforce dominant Western-oriented aesthetics while reducing the visibility of local cultural styles.

This illustrates how recommendation systems may contribute to cultural homogenization and reduced cultural diversity.

9. Ethical Challenges

The major ethical challenges include: Transparency; Accountability; Fairness and equity; Explainability (Crawford, 2021).

Privacy; Cultural diversity.

Digital media organizations increasingly need effective AI governance frameworks to address these challenges.

10. Seven Major Research Themes

The literature can be classified into seven major research themes.

10.1. AI Ethics and Algorithmic Bias

This is one of the largest areas of research and addresses questions such as: Are algorithmic decisions fair? How can discrimination be prevented; What responsibilities do AI developers have? Can algorithms be considered ethically accountable?

As AI becomes increasingly autonomous, fairness, transparency, accountability, and respect for human rights become increasingly important.

10.2. Sources of Algorithmic Bias

Major sources include:

Biased data: Historical discrimination in data may be learned by algorithms.

Developers: Programmers may unintentionally introduce personal assumptions.

Algorithm design: Model selection may favor certain groups.

System use: Users may misinterpret or misuse algorithmic outputs.

10.3. Bias Detection and Measurement

Researchers have developed metrics to detect and measure algorithmic fairness, including: Demographic Parity; Equal Opportunity; Equalized Odds; Predictive Parity; Error Rate Balance.

However, these fairness criteria cannot always be achieved simultaneously. Therefore, developers often face trade-offs among competing definitions of fairness.

The literature has largely focused on technical and ethical aspects of algorithmic bias, while behavioral and organizational issues, particularly users' perceptions of fairness and their

acceptance or rejection of automated decisions, remain comparatively underexplored (Richardson & Gilbert, 2021).

10.4. Mitigation of Algorithmic Bias

Bias mitigation strategies can be divided into three stages.

Pre-processing: Removing or reducing bias in datasets; Balancing representation; Cleaning data; Re-sampling data.

In-processing: Introducing fairness constraints; Modifying objective functions to balance accuracy and fairness; Developing fairness-aware machine learning models.

Post-processing: Recalibrating classification results; Adjusting decision thresholds; Conducting human review before final decisions.

These approaches may reduce bias but cannot guarantee its complete elimination because the roots of bias may be social or organizational rather than purely technical.

10.5. Algorithmic Transparency and Accountability

Algorithms affecting individuals in areas such as employment, lending, insurance, healthcare, and criminal justice should not operate as completely unexplained "black boxes."

Transparency involves more than revealing source code. It includes: Explaining data sources; Clarifying decision-making processes; Identifying responsibility when errors occur; Allowing individuals to challenge automated decisions (Dimakopoulos, 2015).

10.6. Legal and Regulatory Issues

The literature has examined legal frameworks governing AI and algorithms, including the European Union's General Data Protection Regulation (GDPR), which provides safeguards concerning: Personal data protection; Individuals' rights concerning data use; Certain rights related to automated decision-making; Organizational accountability.

Research has also examined legislative initiatives in the United States and other jurisdictions.

However, legislation alone is insufficient. Effective governance also requires organizational practices and institutional cultures committed to fairness and transparency.

10.7. Behavioral and Organizational Consequences

This theme is particularly important because it focuses on human interaction with algorithms.

Key questions include: Do users trust algorithmic decisions? Do they accept AI recommendations? How does perceived fairness influence system use? What makes users accept or reject algorithmic recommendations?

These behavioral dimensions are as important as algorithm development itself because final outcomes often depend on how users perceive the fairness and transparency of AI systems (Starke, Baleis, Keller, & Marcinkowski, 2021).

11. Practical Strategies for Reducing Algorithmic Bias

Effective solutions include:

Diverse Training Data: Develop balanced datasets representing different cultures and communities across East Asia.

Fairness Testing: Conduct algorithmic audits and fairness testing before deployment.

Human Oversight: Editors and specialists should review AI-generated content.

Explainable AI (XAI): Provide clear explanations for AI recommendations and decisions.

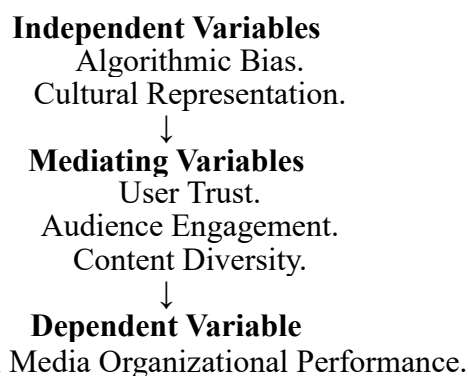
Inclusive Development Teams: Employ AI developers and experts from diverse cultural backgrounds.

Continuous Monitoring: Regularly evaluate algorithmic performance to detect and correct emerging biases.

Government Regulation: Develop ethical standards and regulatory frameworks governing AI use in media organizations.

12. Proposed Conceptual Framework

The proposed framework includes:



Performance indicators include: Revenue; Audience growth; User retention; Brand reputation; Market competitiveness.

The proposed relationship can be summarized as:



13. Conclusion

Artificial intelligence offers significant opportunities for digital media organizations in East Asia, including improved efficiency, personalized content delivery, and enhanced audience engagement. However, algorithmic bias and inadequate cultural representation remain important challenges.

AI systems trained on imbalanced datasets may reinforce stereotypes, reduce content diversity, undermine public trust, and ultimately affect organizational performance.

To achieve sustainable growth, digital media organizations should adopt culturally diverse datasets, conduct fairness and bias audits, strengthen human oversight, and develop transparent AI governance frameworks.

Addressing these issues can improve ethical outcomes while strengthening the competitiveness of digital media organizations in the rapidly evolving East Asian media landscape.

Based on the findings of previous studies, several practical recommendations can help digital media organizations in East Asia reduce the impact of algorithmic bias and improve organizational performance. First, organizations should develop more representative training datasets that incorporate multiple local languages and cultures rather than relying on a single language or cultural context. Second, regular algorithmic audits should be conducted to ensure fairness and to identify potential biases at an early stage. In addition, the principles of Explainable Artificial Intelligence (XAI) should be applied so that users can understand why the system has generated a particular recommendation. Fourth, human oversight should be maintained, particularly in sensitive decisions related to content publication and distribution. Furthermore, organizations should build culturally diverse development teams and promote adherence to transparent and fair AI governance practices. Accordingly, the proposed model establishes a link between algorithmic bias and cultural representation, public trust and engagement, and, ultimately, the organizational performance of digital media organizations in East Asia.

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